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Electric Utility Capacity Expansion and Energy Production Models for Energy Policy Analysis

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ELECTRIC UTILITY CAPACITY EXPANSION AND ENERGY PRODUCTION MODELS FOR ENERGY POLICY ANALYSIS

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ABSTRACT

This report describes electric utility capacity expansion and energy production models developed for energy policy analysis. The models use the same principles (life cycle cost minimization, least operating cost dispatching, and incorporation of outages and reserve margin) as comprehensive utility capacity planning tools, but are faster and simpler. The models were not designed for detailed utility capacity planning, but they can be used to accurately project trends on a regional level. Because they use the same principles as comprehensive utility capacity expansion planning tools, the models are more realistic than utility modules used in present policy analysis tools. They can be used to help forecast the effects energy policy options will have on future utility power generation capacity expansion trends and to help formulate a sound national energy strategy. The models make renewable energy source competition realistic by giving proper value to intermittent renewable and energy storage technologies, and by competing renewable technologies against each other as well as against conventional technologies.

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INTRODUCTION

In 1990 and 1991, the U.S. Department of Energy formulated the first National Energy Strategy (U.S. Department of Energy, 1991). National energy strategies will become increasingly important as the world's fossil energy resources are depleted and as emerging nations increase their demand for these diminishing resources to fuel economic growth. The strategies will also be key elements in addressing environmental and economic competitiveness issues associated with developing and using energy sources. Formulating sound strategies will require using sound tools to project the likely effects energy strategy policies will have on energy production and consumption.

This report describes the electric utility capacity expansion and energy production models, collectively referred to as CEEP (Capacity Expansion and Energy Production), developed at Sandia National Laboratories. The models were developed as part of a project sponsored by the Department of Energy's Office of Utility Technologies and Office of Planning and Assessment. The CEEP models are designed to help forecast the effects energy strategy policies will have on future electric utility capacity expansion trends. A primary objective of our modeling task was to make renewable energy source competition realistic by giving proper value to intermittent renewable and energy storage technologies, and by modeling their competition against each other as well as against conventional technologies.

The CEEP models use the same principles as comprehensive utility capacity planning tools:

1. Power from intermittent sources is dispatched when it is available.
2. Storage units are dispatched using a strategy which minimizes system operating cost.
3. Power from dispatchable sources is dispatched based on merit order; that is, loads are met using the lowest operating cost sources.
4. Existing capacity, forced outages, scheduled outages, and required reserve margin are an integral part of capacity expansion decisions.
5. Capacity expansion is determined by finding the minimum total future life cycle cost system which satisfies the load.

The CEEP models are faster and simpler than comprehensive utility capacity planning tools. Speed and simplicity are important because the models will be used in parametric studies where multiple runs in short periods of time are required. The models are not designed for detailed utility capacity planning. They are designed to accurately forecast trends on a regional level.

Several comprehensive electric utility capacity expansion planning models have been developed, and some give proper value to intermittent sources. One of these is EGEAS (Electric Generation Expansion Analysis System) developed by EPRI (Electric Power Research Institute, 1982). EGEAS is used extensively by many of the largest U.S. utilities and is an excellent tool for planning capacity expansion for an individual utility, but it is not suitable for policy analysis on a regional level because of the computation time and detailed input required. Also, it does not account for cost diversity, a spread in cost or perceived cost among utilities. Cost diversity allows a technology to receive some market share even though its most likely cost is higher than those of competitors. CEEP allows for cost diversity. Although not practical for parametric studies, comprehensive models like EGEAS will be important for policy analysis because they can be used to check the accuracy of less comprehensive models.

Because they use the same principles as comprehensive utility capacity expansion planning tools, the CEEP models are more realistic than utility modules used in present policy analysis tools, such as the electric sector in FOSSIL2 (Now named IDEAS). Previous national energy strategy projections have been based on FOSSIL2 (AES, 1991; Aronson, 1991), but FOSSIL2's electric utility module does not follow utility capacity expansion principles and may not make reliable capacity expansion projections. A few of FOSSIL2's shortcomings are listed below:

1. FOSSIL2 does not adequately consider the difference between dispatchable and intermittent sources. An intermittent source does not have the same value to a utility as a dispatchable source, even though they have equal busbar energy costs, because intermittent sources may not be available when power is needed.
2. FOSSIL2 artificially divides a load duration curve into two areas: peak and a combination of base and intermediate. A logit apportionment is used to determine the market share of competing sources within each area. Competing sources compete at different capacity factors. Since sources do not compete at the same capacity factor, they do not provide the same service. For the logit apportionment to be valid, all competitors must provide the same service; thus, the competition is not valid and may not give rational results.
3. FOSSIL2 assumes a uniform 20% reserve margin. Using a fixed reserve margin does not accurately account for changes in a load duration curve's shape and consequent changes in reserve margin requirement caused by the introduction of intermittent sources, demand management, or storage.
4. FOSSIL2 does not treat intermittent sources as negative loads. The negative load methodology is generally used for utility capacity planning and is an analytically sound way to alter a load duration curve in response to the addition of intermittent energy sources.

The CEEP capacity expansion and energy production models were developed to be used as modules in more general utility models. Two utility models developed at Sandia incorporate the CEEP models as modules. One, REPAM, is a detailed regional model parameterized for

California, and the other TFRM is a much less detailed but geographically more general model for the ten federal regions comprising the United States. These models use what we call a utility driver module which steps through time; provides load, asset, and economic data; calls upon the capacity expansion model at each time step to provide capacity expansion projections; and calls upon the energy production model to estimate the energy generated by each generation technology. The energy production model is called upon by both the utility module driver and the capacity expansion model. The capacity expansion model calls upon the energy production model to generate operating cost information.

In summary, CEEP is simpler and faster than comprehensive utility capacity expansion planning tools like EGEAS, and it is more realistic than existing utility modules currently used for policy analysis like the utility sector in FOSSIL2. It accurately projects capacity expansion trends (as will be seen in the validation section of this report) and will be a valuable tool for energy policy analysis and for helping to develop sound National Energy Strategy policies. An overview description of the models is given in the following sections, and a detailed mathematical description is given in Appendix A.

ENERGY PRODUCTION MODEL DESCRIPTION

The energy production model operates in three steps. First it dispatches intermittent source power by treating intermittent sources as negative loads; second, it optimizes the use of storage to minimize system operating cost and dispatches storage power by treating discharge power as a negative load and charge power as a positive load; and third, it dispatches dispatchable source power using merit order. A utility driver module supplies the energy production model with an hourly load profile. The driver module also supplies normalized hourly power generation profiles for each intermittent technology. Note that the model treats intermittent sources, dispatchable sources, and energy storage separately. It does not presently incorporate sources with dedicated storage such as solar central receiver with salt storage systems.

Intermittent Source Energy Production

The hourly power generated by an intermittent source is equal to its rated capacity multiplied by its normalized generation profile. A "net" load profile is generated by subtracting the hour-by-hour power production of each intermittent source from the given load profile; thus, an intermittent source is treated as a negative load. Since intermittent source generation profiles are controlled by meteorological conditions and not by utilities, they are dispatched when available, and treating them as negative loads is appropriate. Criticisms of the negative load method are generally rooted in valid arguments concerning statistical variation. Hourly values of intermittent source power are not instantaneous. They are averages over the hour. Furthermore, monthly or weekly averages of hourly averages are often used for analysis to avoid using a full year's worth of hourly data. Averaging may destroy statistical variation, and statistical variation is needed to give proper capacity value to an intermittent source. Averaging tends to over-value intermittent source capacity. While simple averaging introduces systematic errors, the number of intermittent source power generation data points can be reduced and intermittent sources can be treated as negative loads, without introducing significant errors, if adequate statistical variation is maintained. This subject is discussed further in Appendix B.

Storage Energy Production

The use of storage is optimized to minimize the utility's operating cost. The general rule is that the operating cost of the source displaced must be greater than the operating cost, divided by storage efficiency, of the source used for recharge. To optimize storage use, the model arranges the net loads for a single day from largest to smallest. The largest load is paired with the smallest. The second largest load is paired with the second smallest and so on until all 24 loads have been paired. Starting with the highest-lowest pair, storage power is subtracted from the high member of the load pair (discharge), and power divided by efficiency is added to the low member of the pair (recharge). The marginal value of energy displaced (which depends on the lowest operating cost technology displaced) is compared to the marginal value of energy used for

recharge (which depends on the highest operating cost technology used for recharge). If the net marginal value is positive, we move to the next load pair. If the net marginal value is negative, we reduce the power supplied by storage until we reach a net marginal value which is positive. This process avoids displacing an energy source and later recharging at an efficiency loss with the same source. It also avoids displacing one source and recharging with a higher operating cost source. We step down the load pairs until energy storage capacity is reached or until storage use is no longer cost effective.

This process is nearly but not entirely optimum. It is not entirely optimum because we have restricted discharge and recharge decisions to hour pairs and do not optimize over multiple hours.

The above process is repeated for each day to generate a net load profile. At this point, the net load profile accounts for the gross load, intermittent source generation, and storage discharge and charge.

Dispatchable Sources

The energy production model calculates the energy generated by each dispatchable source. The energy generated by each source is determined by minimizing the system's total operating cost. We start with a net load profile and develop a net load duration curve from it by arranging the individual loads in decreasing order, resulting in a curve similar to that in Figure 1. The vertical axis values are power, or load. The horizontal axis values have been transformed from hours into that fraction of the year in which power exceeds the associated vertical axis value. The area under the net load duration curve is the total energy, in kW-Yr, which must be supplied by the dispatchable technologies. Technologies (or sources) are arranged in merit order. That is, the ones with the lowest operating cost are dispatched to operate at the highest capacity factor and to provide the most energy. This scheme minimizes the utility's operating cost. The merit order for a hypothetical system is illustrated in Figure 1 which shows a net load duration curve with the utility's capacity arranged in merit order beneath it. For this example, nuclear plants have the lowest operating cost and are dispatched first. The point where the nuclear line intersects the vertical axis is equal to nuclear rated capacity multiplied by its availability (1 - forced outage rate).

Capacity has been derated by availability because the nuclear plants' average power over time will be equal to their rated capacity multiplied by availability. Coal 1 has the second lowest operating cost and is dispatched second. In this example, nuclear power is used at all times. Coal 1 and Coal 2 are next in the merit order and are used most of the time, but there are times when their full capacity is not needed to meet the utility's load. Gas combined cycle plants are next in the merit order followed by gas combustion turbines. Combustion turbines are used only when the combined efforts of the other plants are not sufficient to meet the utility's load. They generate the least energy because their operating costs are highest. Keep in mind that this is a hypothetical example and that other technologies may be included in the merit order and their

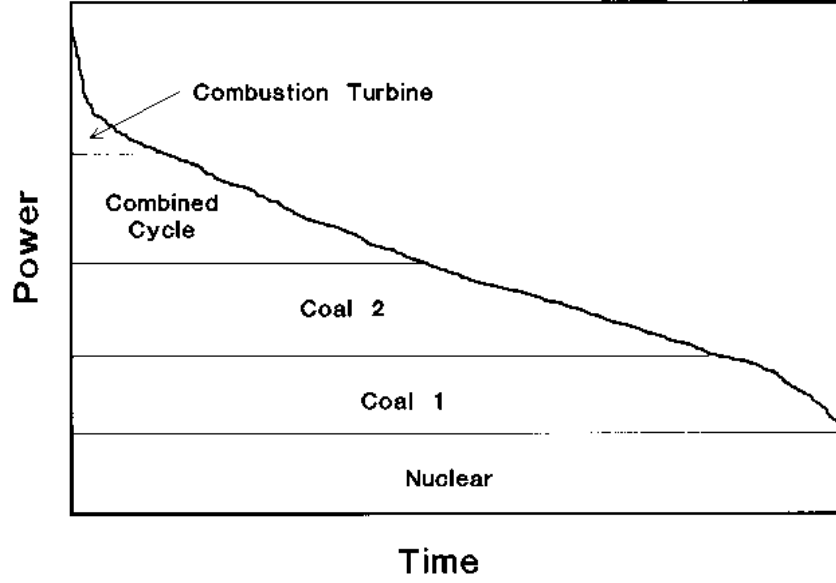


Figure 1. Load Duration Curve and Merit Order

relative positions in the merit order may be different than illustrated here. The energy generated by each technology is the area shown in its band under the load duration curve; however, it may be necessary to subtract energy to account for scheduled maintenance outages. The algorithms used to compute energy generation, including the effects of maintenance outages, are given below.

The maximum energy a technology (technology i) can generate, E_{im} , is given by Equation 1. E_{im} is the maximum energy that can be generated by technology i since it is the product of technology capacity P_i , and the fraction of time the technology is available to operate $(1 - \alpha_i)(1 - \beta_i)$. Since E_{im} is in kW-yr, we have not multiplied by operating time.

$$E_{im} = P_i(1 - \alpha_i)(1 - \beta_i) , \quad (1)$$

The energy a technology is called upon to generate, E_{ig} , is given by Equation 2 and is equal to the area of the load duration curve below its derated capacity value minus the energy generated by preceding technologies.

$$E_{ig} = \int_0^{U_i} u(\lambda) d(\lambda) - \sum_{n=1}^{i-1} E_n \quad (2)$$

$$U_i = \sum_{n=1}^i P_n(1 - \beta_n) \text{ if less than } \Lambda, \quad (3)$$

$$= \Lambda \text{ otherwise ,}$$

the energy actually generated, E_i , is the smaller of these two values.

$$E_i = \text{the smaller of } E_{im} \text{ and } E_{ig}, \quad (4)$$

where: E_i is energy generated by the i^{th} technology in kW-Yr,

P_i is the rated capacity of the i^{th} technology in kW,

α_i is the fraction of time lost for scheduled maintenance,

β_i is the fraction of time lost to forced outages,

U_i is total derated capacity up through technology i in kW,

$u(\lambda)$ is the inverse of the load duration curve function,

Λ is the peak system load (kW).

The average maximum power that technology 1 can generate is $P_1(1 - \beta_1)$ since, on the average, fraction β_1 of its units are not available due to forced outages. Notice that this availability does not include scheduled maintenance because we assume that scheduled maintenance is performed when the unit is not needed to meet the load. Technology 1 is called upon to produce energy equal to E_{1g} , the area under the inverse load duration curve between power level 0 and $P_1(1 - \beta_1)$. Scheduled maintenance may prevent it from producing that much energy if there is not enough time to service its units when demand is low.

The inverse load duration curve, $u(\lambda)$, has power level as the independent variable and time (fraction of the year) as the dependent variable. E_1 is the lesser of E_{1m} and E_{1g} and is the energy generated by technology 1. Technology 2 is called upon to generate the energy under the load duration curve between power levels 0 and $P_1(1 - \beta_1) + P_2(1 - \beta_2)$ minus the energy generated by technology 1. Like technology 1, it is limited by its combination of scheduled and unscheduled outages. We can repeat this process with subsequent technologies until the load has been satisfied. Some units may not produce energy regularly but must still exist to satisfy the system's reserve margin.

This dispatching model which derates capacity and integrates under the load duration curve is an approximation to reality. A probabilistic method such as the Baleriaux method used in EGEAS is more rigorous. We compared the two methods (Appendix B) and concluded that while our integration method underestimates the energy generated by peaking plants, it is sufficiently accurate for policy analysis.

CAPACITY EXPANSION MODEL DESCRIPTION

The capacity expansion model receives utility generation asset, load, and technology cost information from the utility driver module and selects the combination of new dispatchable, intermittent, and storage capacity which will minimize the sum of levelized annual capital cost for new plants plus total levelized annual future operating costs for all plants. This minimization will result in the lowest electrical generation cost for the utility system. A flow diagram of the model is shown in Figure 2.

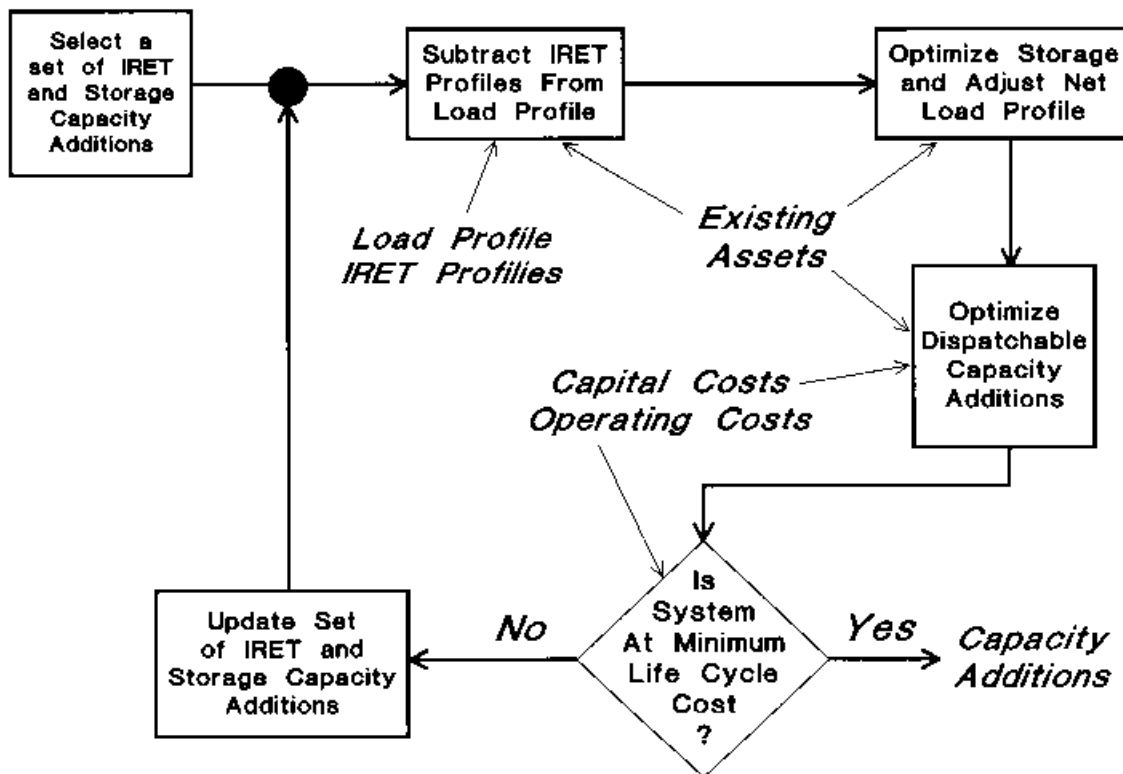


Figure 2. Capacity Expansion Module

Capacity expansion starts with a trial set of intermittent and storage capacity additions. Intermittent source generation is subtracted from the utility's load profile. Storage operation is optimized with generation subtracted from and recharge added to the utility's load profile. The model organizes the resulting net load profile into a load duration curve. Next, the model selects the mix of dispatchable technology capacity additions which minimizes the sum of levelized annual capital cost for new assets plus levelized annual operating cost for all (new and existing) assets accounting for cost diversity (cost uncertainty).

The model selects another trial set of intermittent and storage additions and repeats the above process. Trial sets of intermittent and storage additions are selected using a pattern (Haskell, 1978) search procedure. The search is repeated until the set of intermittent, storage, and

dispatchable technology additions which minimizes total system cost is located. The resulting set of new capacity additions is returned to the utility driver module.

Minimum Levelized Annual Cost

The object of the capacity expansion model is to find the set of new capacity additions which minimizes the sum of levelized annual capital costs for new capacity additions plus levelized annual operating cost for all (new and existing) capacity. Capital cost is expressed as levelized annual cost per unit of capacity (\$/kW-Yr). Operating cost is expressed as levelized annual cost per unit of electrical energy generation (\$/kW-Yr). Annualized capital cost and annualized operating cost for each technology are supplied by the utility driver module. The dispatching model, described above, supplies the annual electrical energy generation for each technology.

Total system future life cycle cost is given by Equation 5 and can be minimized rigorously by optimizing the technology mix for new capacity.

$$C = \sum_i [C_{ci}B_i + C_{oi}E_i(B_i + F_i)], \quad (5)$$

where: C is the total future system levelized annual cost (\$/Yr),

C_{ci} is the levelized annual capital cost of technology i (\$/kW-Yr),

B_i is the new capacity of technology i (kW),

C_{oi} is the levelized operating cost of technology i (\$/kW-Yr),

E_i is the energy generated by technology i (kW-Yr/kW-Yr), and

F_i is the existing capacity (including capacity under construction) of technology i (kW).

Conceptually, the problem is to find the set of B_i values which minimizes C and, at the same time, satisfies the utility's load.

Net Load, Load Duration Curve, and Reserve Margin

The model starts with an hourly load profile provided by the utility driver module. A trial set of new assets for intermittent sources and storage is selected and intermittent power generation for both existing and trial new assets is subtracted from the load profile. Storage discharge is subtracted from and recharge is added to the profile as described in the dispatching section for

both existing and trial new storage. The resulting net profile is organized into a net load duration curve.

We define a modified "reserve margin," r , in Equation 6.

$$r = \sum_i (1 - \beta_i) P_i / \Lambda \quad , \quad (6)$$

where β_i is forced outage rate for dispatchable technology i ,

P_i is rated capacity (kW) for dispatchable technology i , and

Λ is peak load in kW.

It is a modified reserve margin because standard definitions of reserve margin do not include forced outage rates.

We derived an expression, Equation 7, for the required value of modified reserve margin.

$$r = 1 + .25(\Lambda_a/\Lambda)^{2.7} \quad , \quad (7)$$

where Λ_a is the utility's average load. Finding accurate values of reserve margin requires finding the total generation capacity which satisfies the utility's loss of load probability or unserved energy requirement. Our algorithm approximates a loss of load probability analysis. We derived it by computing the generation capacity (and thus reserve margin) needed by a hypothetical utility to satisfy a 0.0002 loss of load probability. The utility was composed of a conventional generation capacity mix representative of the United States mix. Modified reserve margin was computed for a variety of exponential load profiles and a PG&E profile, and correlated to the ratio of average to peak load. Equation 7 is the result of fitting this data. The correlation was adequate. For all of the load curve shapes we tried, when Λ_a approached Λ , modified reserve margin, r , always approached 1.25 which we used as an upper bound.

To account for reserve margin, we simply multiply the net peak load, Λ , by r , the modified reserve margin. This forces our expansion algorithm to satisfy the reserve requirement by setting $\sum (1 - \beta_i) P_i$ equal to $r\Lambda$, and it allows the algorithm to optimize new capacity taking the reserve requirement into account. Negligible energy is added by increasing the peak load, so the method does not significantly affect dispatching. The simplified treatment of reserve margin was done to avoid the time consuming task of computing loss of load probability or unserved energy for every set of capacity additions tested. It saves significant computing time.

Dispatchable Technology Expansion Optimization

The model's next step is to find the set of dispatchable sources (including dispatchable renewable sources such as geothermal and biomass) which minimizes levelized annual system cost for the given trial set of new intermittent sources and storage. We have developed a dispatchable technology expansion optimization algorithm which is unique to the CEEP model. To perform the optimization, the area under the net load duration curve is divided among the existing technologies arranged in merit order with the lowest operating cost technologies at the bottom and the highest at the top. The new capacity required, called the capacity "gap," is equal to the difference between the peak net load (adjusted for reserve margin) and the total existing derated dispatchable capacity. New capacity can be added at the interface between any two existing technologies. Figures 3 and 4 illustrate this for a hypothetical three technology utility. New capacity can also be divided equally among the interfaces of existing technologies. This option is illustrated in Figure 5. The model inserts new capacity between each pair of existing technologies in turn and determines the mix and cost of new capacity for each gap location. The new capacity mix for a particular gap location is determined by a logit apportionment based on each technology's derated levelized annual cost at the capacity factor for the particular gap location. The logit apportionment is defined by Equation 8.

$$B_i = G \frac{(C_{ci}d_i + C_{oi}f)^\gamma}{\sum (C_{ci}d_i + C_{oi}f)^\gamma} \quad (8)$$

where B_i is the new capacity for technology i in kW,

d_i is the technology's derating factor which is a function of capacity

factor and is defined in Appendix A,

G is the total capacity in kW needed,

C_{ci} is the levelized annual capital cost of technology i in \$/kW-Yr,

C_{oi} is the operating cost in \$/kW-Yr of technology i ,

f is the capacity factor for the gap, and

γ is the logit parameter that defines cost variance (we use -10).

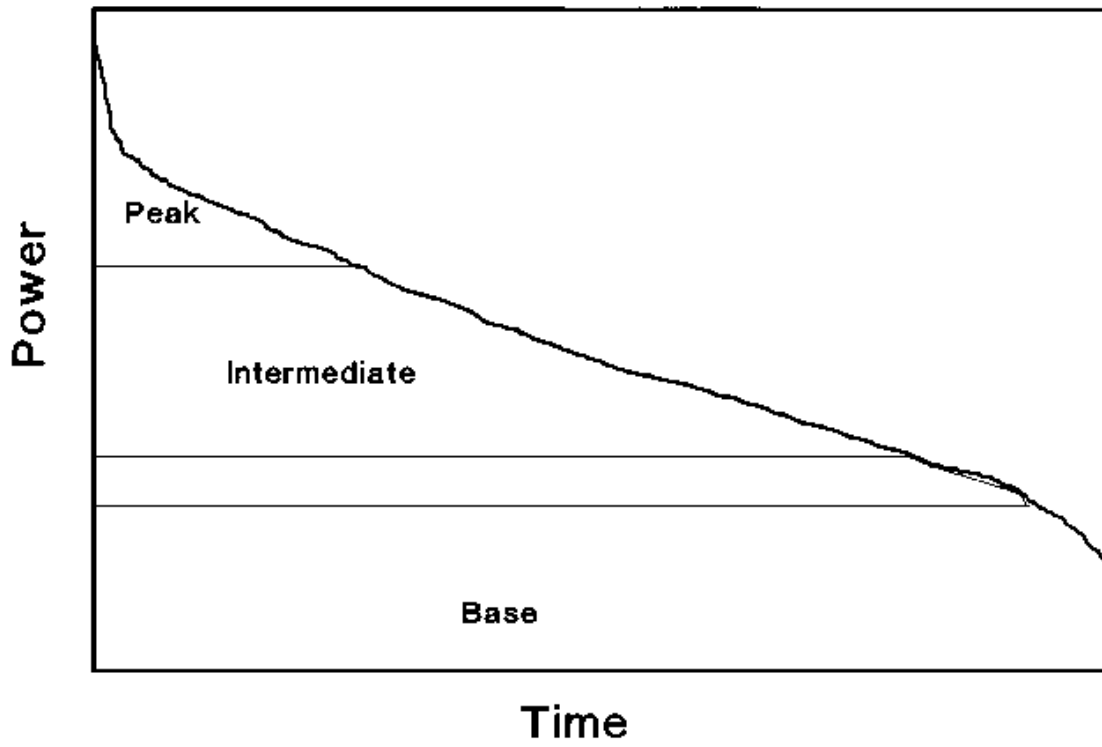


Figure 3. Capacity Expansion Gap Located Between Base and Intermediate

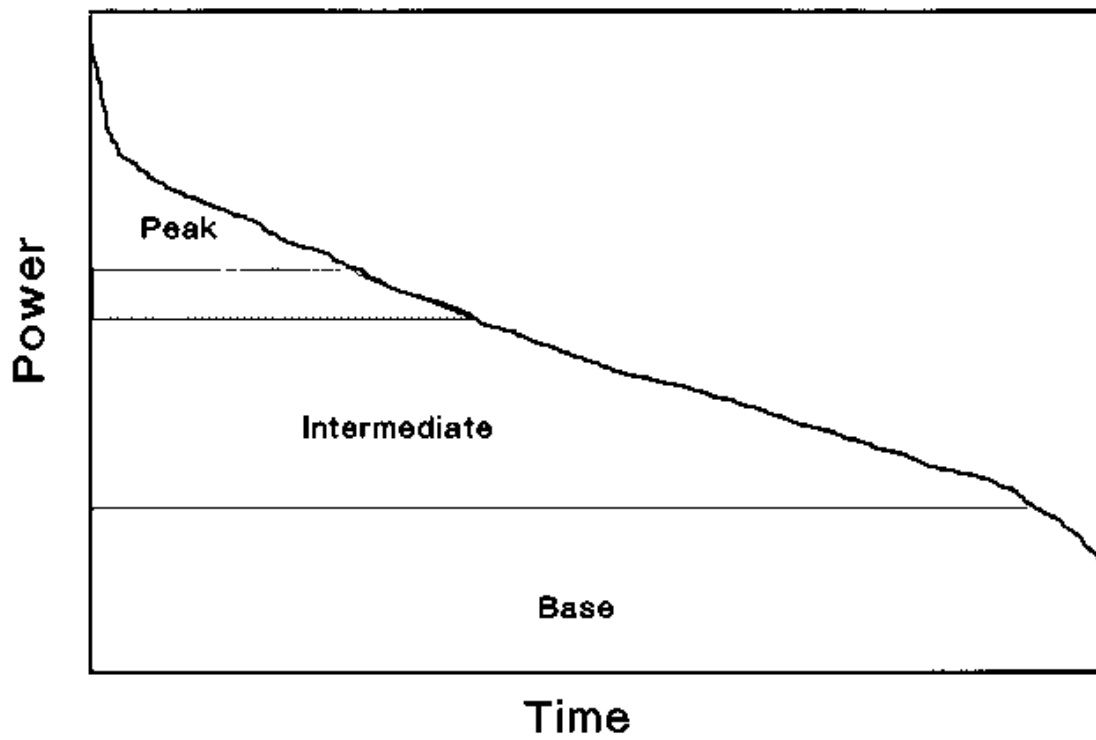


Figure 4. Capacity Expansion Gap Located Between Intermediate and Peak

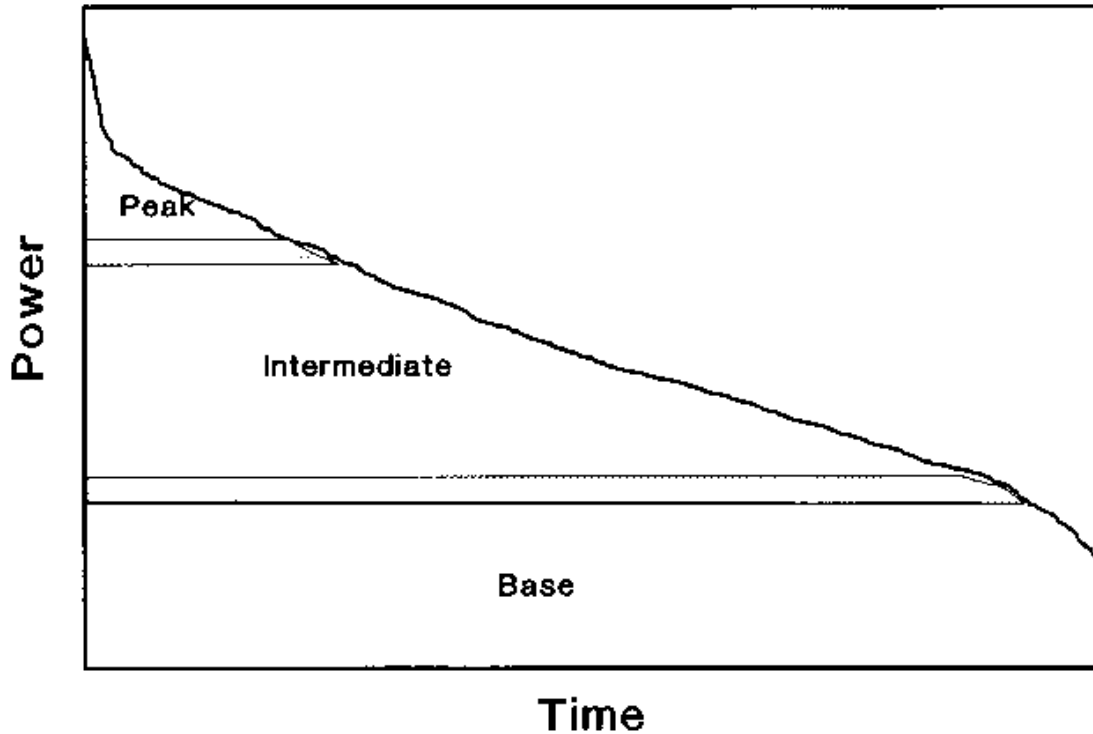


Figure 5. Capacity Expansion Gap Distributed Equally

The logit gives the largest capacity expansion share to the technology with the lowest capital plus operating cost at that capacity factor. The logit accounts for cost diversity by giving all competing technologies a share of the expansion. Technologies which are close in cost to the lowest cost technology will receive relatively large shares while significantly more expensive technologies will receive much smaller shares. Notice that, in this application, the logit apportionment competes all technologies at the same capacity factor; thus, each competing technology provides the same service. This is a consistent application of the logit in contrast to the FOSSIL2 application discussed earlier.

Once new assets for a particular gap location are found, total levelized annual cost for each gap location is calculated using Equation 5 where the energy for each technology is calculated using the dispatching model. Total system levelized annual cost is calculated for each gap location and the gap location with the lowest total cost is selected. If the utility system is short on base capacity, the algorithm will tend to select a "gap" with a high capacity factor. If peak capacity is needed, a low capacity factor "gap" will be selected. If the utility system is balanced, the distributed "gap" will tend to be selected. This algorithm does not minimize system cost at each individual time step, but it does tend to minimize system cost over several time steps. It is fast and simple, but it tracks a true optimization algorithm developed by Sherali (1985). A

comparison of this method with the Sherali method (modified to account for cost diversity using a Monte Carlo method) is presented in Appendix C.

Intermittent Technology and Storage Expansion Optimization

The above dispatchable capacity optimization gives a minimum cost set of new dispatchable technology capacity additions for the specific trial set of intermittent technology and storage capacity values used. The total system is optimized using a pattern search procedure to identify new trial sets of intermittent technology and storage capacity additions. The optimum set of dispatchable technology additions is found for each intermittent trial set and the process is repeated until the minimum levelized annual cost for the whole system is found. When the optimum system is identified, intermittent and storage capacity values are adjusted to account for price diversity. This adjustment is described in Appendix A.

MODEL VALIDATION ACTIVITIES

Capacity expansion model validation activities to date have consisted of critiques by personnel at the U.S. Department of Energy's Office of Utility Technologies, the National Renewable Energy Laboratory, and the Electric Power Research Institute; comparison of individual algorithms with more rigorous algorithms as noted above and described in Appendix C; and comparison to a test case run on EGEAS. EGEAS (Electric Generation Expansion Analysis System) is a utility capacity planning tool developed by the Electric Power Research Institute and used by many of the U.S.'s largest utilities. EGEAS is a very comprehensive model, and the two models are very different in the level of detail required for operation. CEEP is designed for regional analysis and aggregates similar generation units while EGEAS operates on individual units. CEEP uses cost diversity, EGEAS does not. There are many other differences, but the comparison demonstrated that projected trends for the two models agree very well. We saw differences in timing for the addition of particular technologies, but, over a thirty year period, both models added roughly the same capacity for each type of source. A more detailed discussion of the comparison is given in Appendix D.

In November, 1993, DOE/OUT sponsored a critical review of the TFRM which uses CEEP as its core. The review panel included five experts on electric utilities and utility modeling. Their summary (DOE 1994) of findings is included as Appendix F.

CONCLUSIONS

We have developed electric utility capacity expansion and energy production models, collectively referred to as CEEP, for energy policy analysis. The CEEP models fill a gap between current very general energy models which do not adhere to basic utility capacity expansion principles (such as the electric sector of IDEAS) and detailed, high fidelity models for utility capacity expansion planning (such as EGEAS) which are data intensive and time consuming. CEEP offers both fidelity to the basic principles used in utility capacity planning tools and sufficient speed and parsimony to allow its use in general energy models. The CEEP models are not designed for detailed utility capacity planning, but they can be used to project trends on a regional level. The models give proper value to renewable sources and compete them against each other as well as against conventional sources.

Projections from CEEP for a standard EGEAS test case have been compared to projections from EGEAS with very good agreement between the trends. Other validation activities include obtaining critiques from NREL, DOE, and EPRI personnel; a critical review by a panel of utility experts; and comparing individual algorithms from CEEP with more rigorous algorithms. From these activities, we conclude that the CEEP models accurately project trends and should be a valuable tool for energy policy analysis.

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APPENDIX A. Mathematical Description of the Energy Production and Capacity Expansion Modules

Introduction

In this appendix we describe in detail the mathematical algorithms of the energy production and capacity expansion modules. The modules are coded in FORTRAN. The FORTRAN symbols associated with the mathematical variables are given in a table at the end of the appendix. Every technology analyzed in the modules falls into one of two classes: intermittent, renewable, non-dispatchable technologies, called **IRETs**, and dispatchable technologies, called **DTs**. Renewable technologies such as biomass and geothermal are in the dispatchable class, as are fossil burning technologies. Other renewable technologies with large associated storage should also be considered dispatchable. Non-dispatchable technologies are photovoltaics, solar thermal, and wind (all without storage), and energy storage, **ES**. Hydro may be placed in either class, depending on the particular application; however, care must be taken to define its properties properly in either assignment. The modules can treat any number of **IRETs** and **DTs**, with running time and computer size being the only valid limitation, but at least one **IRET** and three **DTs** must be used. In addition, only one of the **IRETs** may be energy storage.

Any self-consistent set of units may be used. In the discussions we will assume that power is in kw, all costs in \$/kWyr, and energy in kWyr. Another consistent set of units would be GW, \$M/GWyr, and Gyr. All energy units are on a per year basis.

A call to the energy production module yields the least-cost energy production of the simulated system for the current one-year period; given the current demand, and the properties and current on-line capacities of the various technologies. By “current year” we mean the current simulation problem time. A call to the capacity expansion module yields the new capacity additions whose construction should be completed in the future year in order to satisfy the anticipated demand in that future year. By “future year” we mean some year in the future from the current year. The construction times for the technologies are not considered by the capacity expansion module. Management of how much of the new capacity additions suggested by the module are actually constructed and when their construction is initiated are functions of the utility module which calls the capacity expansion module. The capacity expansion module uses the estimated future load demand and technology costs are properties in the future year, as well as the estimated capacities and properties of the various technologies that will be on-line at the future year, and returns new capacity additions that will satisfy the future demand in a least-cost fashion. Because the algorithms for both modules are necessarily simple and heuristic, they are sub-optimal. However, they are very near optimal under the constraints of the model.

We assume that we are considering $I > 2$ **DTs** and $J > 0$ **IRETs**. The subscript $I = 1, 2, \dots, I$ is used to identify the **DTs** and $j = 1, 2, \dots, J$ to index the **IRETs**. For convenience, we use the special notation \sum_{ξ} to denote the sum on the index ξ .

Energy Production Algorithm

This module computes the amount of energy produced by each technology to satisfy the current yearly demand; that is, it computes the total energy that will be dispatched by each technology over the current year. We first explain energy production without energy storage, which is discussed later.

Input:

- L_t Load demand table, in kW, as a function of time-of-year t , $t = 1, \dots, T$. This table, of $T > 0$ entries, gives the current average load power demand for each $1/T$ part of the year. The table may be in any time-of-year order, but the order must be consistent with the same time-of-year order as the **IRET** production supply tables. In the special case of energy storage, the order is somewhat more restrictive, see section **A.2a**.
- P_j Maximum rated power capacity of the existing, on-line, j -th **IRET** (kW).
- S_{jtl} The current production supply function of the j -th existing, on-line, **IRET** over time the t -th time interval (nondimensional). Over the t -th time interval the j -th **IRET** produces $P_j S_{jtl}$ kW of power, and $P_j S_{jtl}/T$ kW_y of energy. These functions apply to non-**ES IRETS** only.
- c_{oi} Operating cost of the i -th **DT** is (\$/kW_y).
- P_i Maximum power capacity of the existing, on-line, i -th **DT** (kW).
- f_i Forced availability rate of the i -th **DT** (one minus the forced outage rate).
- s_i Scheduled availability rate of the i -th **DT** (one minus the scheduled outage rate).
- e_{ps} Energy storage efficiency, $0 < e_{ps} < 1$.
- r_{ps} Fraction of a day that **ES** is able to operate at full power output, $0 < r_{ps} < 0.5$.

Output:

E_j Total energy produced by the j -th **IRET** in the current year (kW_y).

E_i Total energy produced by the i -th **DT** in the current year (kW_y).

The first operation of the module is to sort the DT's in merit order: that is, in increasing operating cost order. At the completion of the year's dispatching the technologies are put back in the original order, along with the energy results, so the sort is transparent to the calling module. We therefore assume that $i = 1$ is the index of the lowest operating cost technology, $i = 2$ is the index of the next-to-lowest operating cost technology, etc. The **DTs** are dispatched in increasing index i order.

The **IRETs** are dispatched before the **Dts**, on the assumption that the **IRETs** always have lower operating costs than the **DTs**. The **IRET** energy is subtracted from the load, and the remaining "net" load is dispatched by the **DTs**. The total energy produced for each **IRET** technology is:

$$E_j = \sum_t P_j S_{jtl} / T.$$

The remaining net load function is:

$$\Lambda_t = \max(0, L_t - \sum_j P_j S_{jtl}).$$

The net load function, Λ_t , is sorted into decreasing order, generating a monotonically non-increasing piecewise-step load demand table denoted by Λ_{st} . We wish to create a continuous load demand curve, $\lambda(u)$, as a function of capacity utilization ratio, $0 \leq u \leq 1$, so that the load demand curve may be easily inverted, interpolated, and integrated. The function $\lambda(u)$ is continuous and is piecewise linear between the arguments:

$$u = (t - 1)/T \text{ and } t/T.$$

The values of λ at the $T+1$ equi-spaced values of u where the linear pieces are joined are:

$$\lambda(0) = (3\Lambda_{S1} - \Lambda_{S2})/2,$$

$$\lambda(t/T) = (\Lambda_{St} + \Lambda_{S,t+1})/2, t = 1, 2, \dots, T-1,$$

$$\lambda(1) = (3\Lambda_{ST} - \Lambda_{S,T-1})/2.$$

The generation of $\lambda(u)$ is shown in Figure A-1 for a simple example with $T = 5$. We denote the inverse of $\lambda(u)$ as $u(\lambda)$. The λ and u function have the constraints that :

$$\lambda = 0 \text{ for } u < 0 \text{ and } u > 1,$$

$$u = 1 \text{ for } 0 \leq \lambda \leq \lambda(1),$$

$$u = 0 \text{ for } \lambda < 0 \text{ and } \lambda > \lambda(0).$$

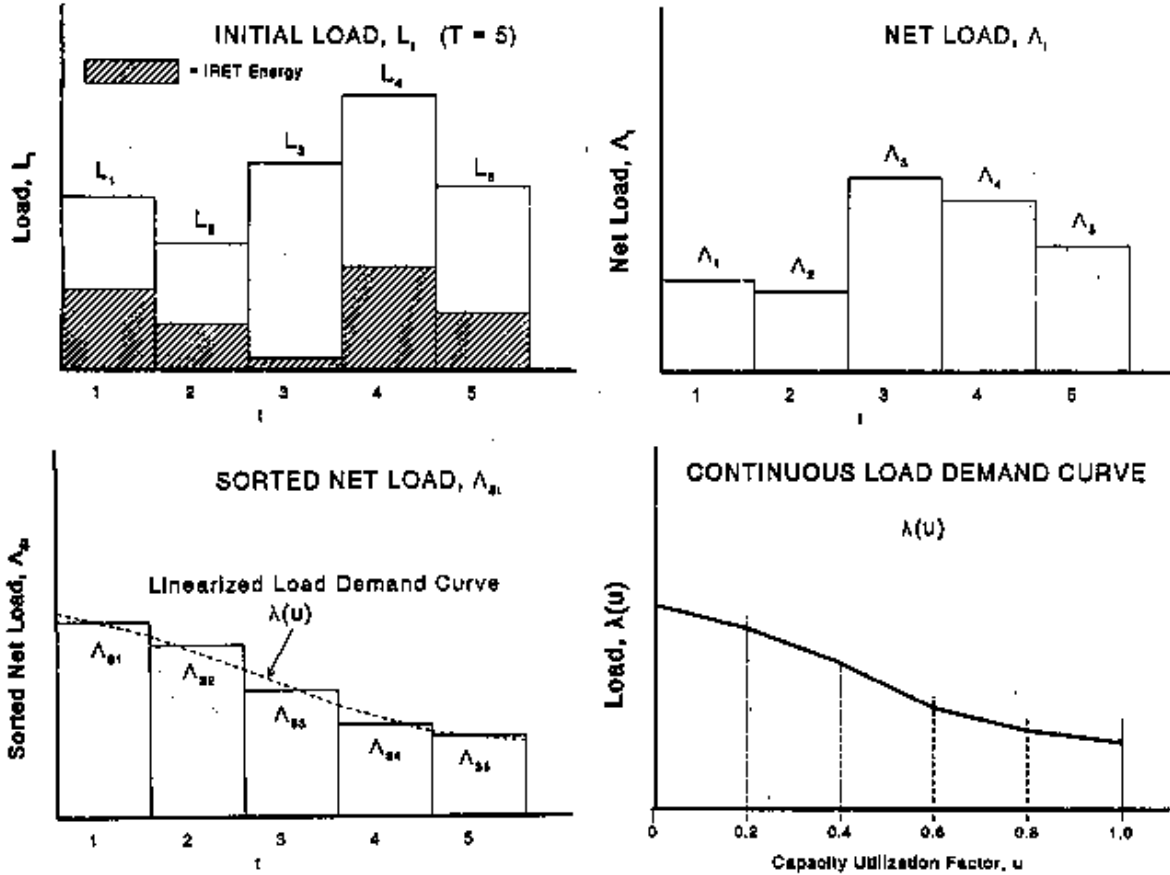


Figure A-1. Load Functions

The **DTs** are now dispatched, in merit order, to satisfy the net load λ . The basic idea in the **DT** is that the average, reliable power generated by each technology, called “effective” capacity (or effective power) is $P_i f_i$ and the maximum energy generated is $P_i f_i s_i$. We assume that scheduled outage for maintenance is done when the technology is not needed to satisfy demand, so that if the capacity utilization factor of the technology is less than the scheduled availability, scheduled outages is not a factor in its energy production.

The energy production is computed in a recursive manner. Let X be the total energy produced and p the total effective power associated with the dispatched energy. Initially, set $x = 0$, $p = 0$, and $i = 1$. The recursion steps are:

1. Set p equal to $p + p_i f_i$.
2. $E_i = \max\{0, \min[p_i f_i s_i, \int_0^p u(\lambda) d\lambda - x]\}$.
3. Set x equal to $x = E_i$.
4. Set i equal to $i + 1$. If $i > I$, quit, else go to step 1.

Energy Production with Energy Storage

Computation of **ES** energy production is complicated by the fact that it is quasi-dispatchable. We assume that **ES** is dispatched in an “optimal” manner on a diurnal basis. The basic concept is that when demand is low during a day the **ES** can be charged by base technologies which have relatively low operating costs; and when demand is high during the same day, the **ES** can be discharged to replace relatively high operating cost technologies. For each day only enough energy is dispatched so that the marginal cost of the energy necessary to charge storage is less than the marginal cost of the discharged energy that would have to be provided by a **DT**. We assume that each day’s energy production is independent of all other days’. Of course, there is an energy efficiency loss in the process.

Assume that one (and only one) of the **IRETs** is **ES**. Given the initial load table, we remove all non-**ES IRET** production to produce a “quasi-net” load table. We then “optimally” dispatch the **ES** energy based on this quasi-net load. Here “optimally” means in an heuristic, least-cost, manner. The **ES** energy is removed from the quasi-net load, and the remaining net load is sorted, the linearized load demand curve is generated, and the **DT** energy dispatched as described in section **A.2**.

If **ES** is a candidate technology, the initial load demand table, L_t , must be contiguous diurnally; that is if a day is defined to be $H > 0$ “hours,” the first H values of L_t are considered to be data for a common day. The next H values are common to some other day, etc. Therefore T must be a multiple of H . Typically, $H = 24$. If the data set consists of Δ days, then we must have $T = H \Delta$.

For convenience, assume that **ES** is the J -th **IRET**, then the maximum power capacity of the **ES** is P_J . Let Q_t be the quasi-net load table with the energy produced by the first $J-1$ **IRET** technologies removed from the load L_t .

$$Q_t = \max(0, L_t - \sum_{\xi=1}^{J-1} P_{\xi} S_{\xi t}).$$

For day δ , $\delta = 1, \dots, \Delta$, let $\tau(\delta)$ be the set of load values associated with day δ , i.e.,

$$\tau(\delta) = \{t \mid H(\delta - 1) < t \leq H\delta\}.$$

The load values for each day, $Q_t, t \in \tau(\delta)$, are processed in pairs. We first process the largest Q_t in the set. We next process the second largest paired with the next-to-the-smallest, etc. There are $H/2$ pairs processed each day. The computed **ES** power output is subtracted from the larger load of the pair, and added (after division by the efficiency, e_{ps}) to the smaller load of the pair.

Let Π denote the cumulative average effective **DT** capacity, and define the $I+1$ abscissa points

$$\Pi_i = \Pi_{i-1} + P_i f_i, \Pi_0 = 0, i = 1, 2, \dots, I.$$

The marginal operating cost as a function of Π , $\kappa(\Pi)$, is a piecewise step function with range

$$\kappa(\Pi) = c_{oi}, \Pi_{i-1} \leq \Pi < \Pi_i,$$

where c_{oi} is the operating cost of the i -th **DT**. That is, the marginal operating cost for each power level is equal to the operating cost of the last technology added or removed by the storage. Let the subscript $h, h = 1, \dots, H/2$, denote the ordered load pairs within the day δ . Let the $A_h(\delta)$ be the high Q_t value of the h -th pair and let $B_h(\delta)$ be the low value. From the definition of the pairing, there is a well-defined pair of mappings of h onto $\tau, t_A(h, \delta)$ and $t_B(h, \delta)$, so for each h in each day a value of h and δ is associated with a unique pair of t values. Let $x_h(\delta)$ be the ES power output for the h -th pair - to be subtracted from $A_h(\delta)$ - and $Y_h(\delta)$ be the power added to the system for the h -th pair - to be added to $B_h(\delta)$. We have

$$Y_h(\delta) = X_h(\delta)/e_{ps}.$$

The algorithm proceeds as follows:

For each day initialize the total available daily **ES** energy output to $W = r_{ps}HP_J$. This is the maximum output the **ES** is allowed per day. Initialize $h = 1$.

1. Find the maximum value of $X_h(\delta)$ such that

a) $0 \leq X_h(\delta) \leq \min(P_J, W)$ and

b) $\kappa[A_h(\delta) - X_h(\delta)] > \kappa[B_h(\delta) + Y_h(\delta)]/e_{ps}$.

If no such $X_h(\delta)$ can be found, $X_h(\delta) = 0$. This step implies that the storage discharge power cannot exceed its rated power and that the total daily energy output cannot exceed the rated storage energy.

2. Set $L_t = Q_t - X_h(\delta)$, $t = t_A(h, \delta)$ and $L_t = Q_t + Y_h(\delta)$, $t = t_B(h, \delta)$.
3. Set $W = W - X_h(\delta)$.
4. Set $h = h + 1$. If $h > H/2$, quit: else go to step 1.

This algorithm optimally dispatches ES energy and produces the net load table, Λ_t , which is dispatched by the **DTs** as described in section A.2. The total energy output of the **ES** is

$$E_J = \sum_{\delta} \sum_h X_h(\delta)/T.$$

Capacity Expansion Algorithm

This module computes the **IRET** and **DT** new capacity additions that satisfy future demand with least-cost. By “new capacity additions” we mean those capacity additions that the capacity expansion module returns as results, which are suggested new capacity in addition to whatever capacity is already committed to be on-line at the future time. The algorithm is heuristic. The cost that is minimized is the total capital cost of the new capacity additions plus the total operating cost of the augmented configuration of technologies. As above, we assume that there are $I > 2$ **DTs** and $J > 0$ **IRETs**. This module also internally sorts the **DTs** in increasing operating cost order, and unsorts the expansion results. The sorting is transparent to the calling module. We therefore assume, as before, that $i = 1$ is the index of the lowest operating cost **DT**, etc. The operating costs of the **IRETs** are considered negligible with respect to the **DT** operating costs, the **IRETs** are not reordered, and they produce as much energy as they can (with the exception of **ES**, see sections A.2a and A.3b). Since the **ES** operating cost does not include the energy cost to charge it, the **ES** operating cost is also considered negligible to the **DT** operating costs.

Input: As before, j refers to **IRETs** and i to **DTs**.

L_t	Future load demand table (kW). These data have the same properties as previously defined, but the values are for future load.
F_j	Maximum power capacity of the j -th IRET that is already committed to be on-line at the future time, before the suggested new capacity (kW). This quantity includes all on-line capacity plus all capacity already under construction that will be on-line at the future time, less retirements.
S_{jtl}	Production supply tables associated with F_j .
S_{jtl2}	Production supply tables associated with j -th new capacity addition. The new capacity additions are allowed to have different supply tables than the existing capacity, F_j .
c_{cj}	Levelized, annualized capital cost of the j -th IRET (\$/kWyr).
c_{oj}	Levelized, annualized operating cost of the j -th IRET (\$/kWyr).
γ_j	Cost diversity parameter for the j -th IRET . Typically, $\gamma_j = -10$.
M_j	Maximum allowed new capacity additions for the j -th IRET (kW). If expansion of the j -th technology is not allowed, $M_j = 0$.

F_i	Maximum power capacity of the i-th DT that will be on-line at the future time, before new capacity additions are added (kW).
c_{ci}	Levelized, annualized capital cost of the i-th DT (\$/kW _y).
c_{oi}	Levelized, annualized operating cost of the j-th DT (\$/kW _y).
f_i	Forced availability of the i-th DT .
s_i	Scheduled availability of the i-th DT .
k_i	A binary variable. If $k_i = 0$, the i-th technology may not be expanded. If $k_i = 1$, the i-th technology may be expanded, without bound. The k_i may change as time changes. At every time step, at least one technology must be expandable!
γ	Cost diversity parameter for all DTs . Typically, $\gamma = -10$.
r_m	A parameter associated with the system reserve margin. Typically, $r_m = 0.25$. Note: r_m is not the reserve margin of the system!

Output:

B_j	Optimum IRET suggested new capacity additions, $0 \leq B_j \leq M_j$ (kW).
B_i	Optimum DT suggested new capacity additions, $0 \leq B_i$ (kW). Note: if $k_i = 0$, then $B_i = 0$.

Since all **IRETs** are assumed to generate all the energy they can, their capital cost and operating cost, per unit capacity, is combined into a single cost for each **IRET**. Let c_j be the combined capital and operating cost of the j-th **IRET** candidate new capacity addition. We call c_j the “nominal” cost (per unit maximum capacity) and define it as

$$c_j = c_{cj} + c_{oi} \sum_t S_{jt2}/T, \text{ for no-ES IRETs, and}$$

$$c_j = c_{cj} + c_{oj}r_{ps}/2 \text{ if the j-th technology is ES.}$$

This latter relationship is based on the assumption that the best estimate of **ES** production is that it will produce half the energy of the maximum allowed. The c_j are fixed for each capacity expansion call and have the units \$/kW_y.

Define:

b_j	A “candidate” new capacity addition for the j-th IRET , $0 \leq b_j \leq M_j$ (kW).
β	The set of candidate IRET new capacity additions, $\beta = \{b_j, j = 1, \dots, J\}$.
K	The minimum total system cost of the candidate configuration, which satisfies the future energy demand, ignoring any capital costs associated with the IRET new capacity additions (\$).
b_i	The candidate new capacity addition for the i-th DT , $0 \leq b_i$, which produces the minimum system cost ignoring IRET costs, K , given a candidate set of IRET new capacity additions (kW).
c	Total system cost of the candidate configuration, consisting of the total minimum system cost, K , plus all capital costs associated with the IRET candidate additions (\$).

β_i A set of candidate **DT** new capacity additions, $\beta_i = \{b_i, i = 1, \dots, I\}$.

θ The function relating β_i to β , $\beta_i = \theta(\beta)$.

If $M_j = 0$, $b_j = 0$; and if $k_i = 0$, $b_i = 0$.

The basic operation of the algorithm is as follows:

1. An initial candidate set of **IRET** new capacity additions, $\beta = \{b_j\}$, is chosen. The code uses zero new capacity additions for all technologies, $\beta = \{0\}$, as the initial set. Note: for all **IRET** candidate sets, $0 \leq b_j \leq M_j$.
2. Given a candidate **IRET** new capacity additions set β , the algorithm finds the **DT** set $\beta_i = \{b_i\} = \theta(\beta)$, which produce K ; that is, the least-cost system given the **IRET**s, as though the **IRET**s had no associated costs. Since the **IRET** operating costs are subsumed into the c_j , K is not a function of the c_j , but of β only (and λ , of course, the net load and costs and properties of the **DT**s, etc.). Therefore, $K = K(\beta)$.
3. The total system cost $c = K(\beta) + \sum_j c_j b_j$, is computed.
4. Using a pattern search method [Haskell and Jones, 1977] a new β set is chosen and c , K , and β_i are recomputed. The search continues until the minimum c is found.
5. Let the β set which minimizes c be $\beta^* = \{b_j^*\}$. An **IRET** price diversity algorithm is then invoked which adjusts β^* to the price-diversified, optimal solution values B_j .
6. The optimal system cost is $c^* = c(B_j)$, the final **DT** new capacity additions are $B_i = \theta(B_j)$, and the final **IRET** new capacity additions are B_j .

Dispatchable Technology Capacity Expansion

Given a trial set of b_j , we first remove the existing and candidate **IRET** production from the (future) net load table. The (future) net load table is

$$\Lambda_t = \max[0, L_t - \sum_j (F_j S_{j1t} + b_j S_{j12})].$$

If one of the **IRET**s is **ES**, a somewhat different procedure is used, see section **A.3b**. The Λ_t sorted, and the continuous, piecewise linear net load demand curve $\lambda(u)$ is created in the same manner as described in the current energy production algorithm section **A.2**, with one difference. To account for reserve margin, the value of $\lambda(0)$, the peak net load, is augmented. Let λ' be the unaugmented value of the peak. As in section **A.2**,

$$\lambda' = (3\Lambda_{S1} - \Lambda_{S2})/2,$$

where Λ_{S1} is the largest value of Λ_t and Λ_{S2} is the next largest value of Λ_t . The peak net load demand, augmented by the reserve margin, is

$$\lambda(0) = \lambda' + \lambda' r_m [\sum_t \Lambda_t / T \lambda']^{2.7}.$$

This relationship has been empirically derived by computing loss-of-load-probabilities for various load shapes (average value to maximum value ratio) and “typical” forced outage rates for fossil technologies.

The total **DT** effective new capacity needed to satisfy the future net demand is

$$g = \max(0, \lambda(0) - \sum_i F_i f_i).$$

We refer to g as the “gap”. If the gap is zero, $b_i = 0$. If $g \neq 0$, we must compute the optimal expansion of the **DTs**. This is accomplished by offering sets of candidate values of the b_i and choosing that set which minimizes the total capital cost of the (**DT**) expansion plus the cost of producing all the energy required by the net load. For I **DTs** we use I candidate sets. the first $I-1$ candidate sets are generated by placing the total gap at load levels which are at the interfaces between the i -th and $i+1$ -th effective capacity. The I -th candidate set is computed by distributing the gap evenly between all **DT** interfaces. Figure **A-2** gives a graphical example of the gap placements for $I = 3$. Let the index n , $n = 1, \dots, I$ denote the n -th candidate set, and let b_{in} be the n -th candidate of the i -th technology.

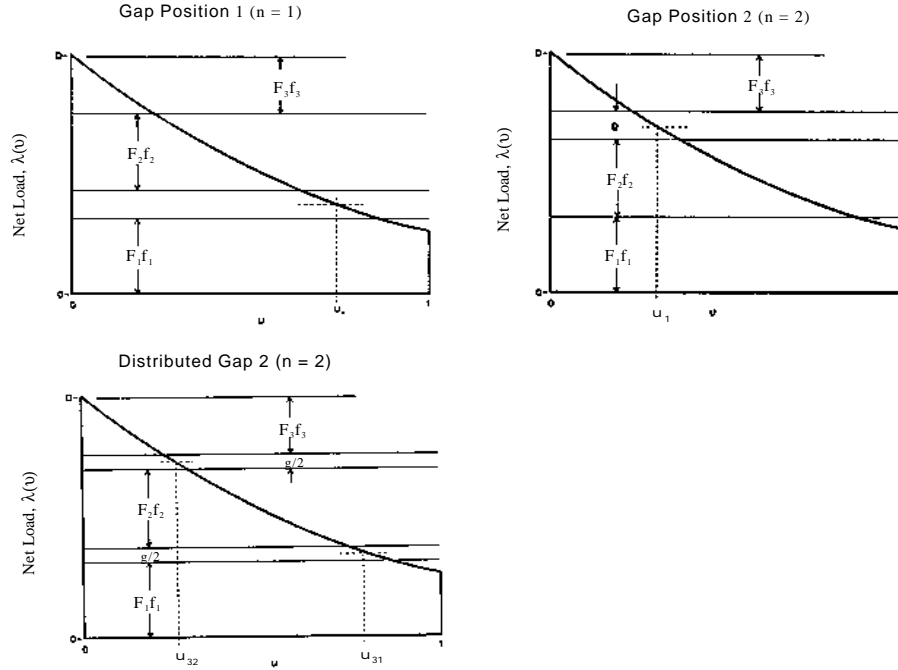


Figure A-2. Graphic Example of Graph Placements

Before computing the b_{in} , each **DT** is assigned a weight which depends on its position in the merit order and whether its immediately adjacent neighbors in the merit order are expandable or not. Recall that the variable k_i is zero if the technology is not expandable, and unity if it is expandable. This variable is fixed at each simulation time, but may vary from time to time. This situation may occur, for example, when some technology may not exist early in a simulation, but comes into existence as time progresses. The situation may also occur if a technology has on-line capacity which is used for energy production but cannot be expanded for non-economic reasons--environmental, political, etc. All (**DT**) expandable technologies compete with all others at every gap position. Therefore, the “inner” technologies, not the first nor the last in merit order, have, have potentially more favorable opportunities to compete than the “outer” technologies. Also, if a technology is expandable and one or both of its neighbors is not expandable, the expandable one has an advantage over its competitors who may have to compete with its neighbors. The weighting scheme is intended to create an even competition among expandable technologies. The weights, W_i , are:

- 1a. If $i = 1$ and $k_2 = 1$, $W_1 = 2k_1$.
If $i = I$ and $k_{I-1} = 1$, $W_I = 2k_I$.
- 1b. If $i = 1$ and $k_2 = 0$, $W_1 = k_1$.
If $i = I$ and $k_{I-1} = 0$, $W_I = k_I$.

- 2a. If $1 < i < I$, and $k_{i-1} = 0$ and $k_{i+1} = 0$, $W_i = k_i/2$.
- 2b. If $1 < i < I$, and $k_{i-1} = 1$ and $k_{i+1} = 0$, $W_i = 2k_i/3$.
If $1 < i < I$, and $k_{i-1} = 0$ and $k_{i+1} = 1$, $W_i = 2k_i/3$.
- 2c. If $1 < i < I$, and $k_{i-1} = 1$ and $k_{i+1} = 1$, $W_i = k_i$.

The various situations above are:

- 1a. Outer technology, competing neighbor.
- 1b. Outer technology, non-competing neighbor.
- 2a. Inner technology, neither neighbor competing.
- 2b. Inner technology, one competing neighbor.
- 2c. Inner technology, both neighbors competing.

Note that if the i -th technology is not expandable, $W_i = 0$.

Let λ_n be the load at the middle of the n -th gap for the first $I-1$ gap positions, and λ_{lm} , $m = 1, \dots, I-1$, be the mid-gap load for each of the distributed gaps, then

$$\lambda_n = g/2 + \sum_{i=1}^n F_i f_i, \quad n = 1, \dots, I-1,$$

$$\lambda_{lm} = (m-.5)g/(I-1) + \sum_{i=1}^m F_i f_i, \quad m = 1, \dots, I-1.$$

Associated with each gap position is a capacity utilization factor. Let u_n denote the capacity utilization factor associated with the first $I-1$ gap positions, and u_{lm} be the factors associated with the distributed gap. All factors are computed by inverting the net load curve in the middle of each gap position. The capacity utilization factors are

$$u_n = u(\lambda_n) \text{ and } u_{lm} = u(\lambda_{lm}).$$

Each new capacity addition candidate value is “derated,” depending its forced availability and the relationship between its scheduled availability and the capacity utilization factor where it may operate. Technologies must be derated because, in order to guarantee some level of dependable power and energy, more capacity than the guaranteed level must be available. The derating function used in the **DT** expansion algorithm is

$$d(i,u) + 1/[f_i \max(1, 1 - u + s_i)].$$

In this formulation, if the capacity utilization factor is less than the scheduled availability, scheduling is not considered.

Apportionment of the b_{in} is accomplished by a logit function, see [Ben-Akiva, 1985], [Reister, 1982], and Appendix E. The logit assumes that each technology exhibits price diversity, and that in the aggregate there is a nonzero probability that any technology can outbid all others for market

expansion. If two technologies' nominal prices are widely apart, the less expensive one will capture most of the market, but if their nominal prices are quite close, they will tend to have nearly equal market shares. The logit formulation avoids “knife-edge” decisions, where, if one price is infinitesimally less than another, the former get all the market share. In addition to addressing the reality of price diversity itself, the logit also implies uncertainty in assumed prices.

The logit formulation assumes that the cost (or price) of all competing technologies are independent random variables whose probability density function is Weibull. The Weibull distribution is defined by two parameters: a location parameter and a shape parameter. If the nominal cost of a technology (location parameter) is c , and its shape parameter is γ ($\gamma < 0$), then the cost distribution has mean and variance

$$\text{Weibull mean} = [\Gamma(1 - 1/\gamma)]c ,$$

$$\text{Weibull variance} = [\Gamma(1 - 2/\gamma) - \Gamma^2(1 - 1/\gamma)] c^2 ,$$

where Γ is the gamma function. For $\gamma = -10$, the mean is $0.95c$ and the standard deviation is $0.1145c$.

The candidate capacity expansion values are

$$b_{in} = g\Omega_{in}d(i, u_n) / \sum_i \Omega_{in}, \text{ for } n < I, \text{ and}$$

$$b_{in} = g \sum_m \Omega_{im}d(i, u_{Im}) / \sum_i \sum_m \Omega_{im}, n = I,$$

where the Ω_{in} and Ω_{im} are the logit weights

$$\Omega_{in} = W_i[d(i, u_n)c_{ci} + u_n c_{oi}]^\gamma, = 1, \dots, I-1,$$

$$\Omega_{im} = W_i[d(i, u_{Im})c_{ci} + u_{Im}c_{oi}]^\gamma, m = 1, \dots, I-1.$$

The energy production required to satisfy the future net load is calculated for each candidate set of new capacity additions. The production algorithm is the same as current energy production described in section A.2 with the future net load as the net load, and the future existing capacity plus the candidate capacity as capacity. Let E_{in} be the energy production of the i -th technology and n -th candidate set. For each n we initially set $X = 0$, $p = 0$, and $I = 1$. The algorithm is

1. Set $p = p + (F_i + b_{in}) f_i$.
2. $E_{in} = \max \{0, \min[(F_i + b_{in})f_i s_i, \int_0^p u(\lambda)d\lambda - X]\}$.
3. Set X equal to $X + E_{in}$.
4. Set $i = i + 1$. If $i > I$, quit, else go to step 1.

Let K_n be the capital cost plus energy cost associated with the n -th DT candidate set,

$$K_n = \sum_i c_{ci} b_{in} + \sum_i c_{oi} E_{in}.$$

The “best” set is that set which yields the minimum value of K_n ; i. e.,

$$b_i = b_{in^*}, \text{ if } K_{n^*} \leq K_1, K_2, \dots, K_I, \text{ i. e., } K = K_{n^*}.$$

In summation, given a candidate set of **IRET** new capacity additions, β , the algorithm computes the set of **DT** new capacity additions, $\beta I = \theta(\beta)$, which minimizes the total expanded system cost as though the **IRET** new capacity additions were free. That minimum cost is $k = k(\beta)$.

Capacity Expansion with Energy Storage

Energy production with energy storage for the future system is essentially the same as for the current system, section **A.2a**, but the definition of the existing **DT** effective capacities used to optimally dispatch the **ES** energy is more complicated. Ideally, the total future capacity of each **DT** is its existing (future) capacity plus its (candidate) new capacity addition, see section **A.2a**. If b_{in} is a candidate set of **DT** new capacity additions, then the definition of cumulative average available capacity for the future candidate system is

$$\Pi_i = \Pi_{i-1} + (F_i + b_{in})f_i.$$

However, since the **DT** new additions depend on the candidate **ES** energy production, and the **ES** energy production depends on the **DT** new capacity additions, we are faced with a circular computation. It would be possible to resolve the computation by an iterative procedure, but this would be too computationally expensive.

We use a simple heuristic to estimate the **DT** new capacity additions with respect to each **IRET** candidate set which uses **ES**. When the capacity expansion module is called, the first **IRET** candidate set is always the zero valued set $\beta = \{0\}$. Let the optimal (minimum k) **DT** set associated with this **IRET** candidate set be $b_{i0} = \theta(\{0\})$, and define the relative new capacity expansion ratios by

$$\rho_i = b_{i0} / \sum_i b_{i0}.$$

For all other candidate **IRET** capacity expansion sets, β , at the same future time, we define the cumulative capacity as

$$\Pi_i = \Pi_{i-1} + (F_i + g\rho_i)f_i,$$

where the gap width g depends, of course, on β . The **ES** energy is then dispatched as in section **A.2a** with Π_i defined as above.

IRET Search Space Constraint and Price Diversity

As described above, for each candidate **IRET** new capacity addition set, $\beta_i = \theta(\beta)$, a (minimum) cost associated with the **DT** new capacity expansion capital costs and future energy production costs, $K = K(\beta)$, and a total system cost

$$c = K(\beta) + \sum_j c_j b_j.$$

Using a pattern search [Haskell, 1978], we find the set $\beta^* = \{b_j^*\}$ which minimizes c subject to the constraints, $0 \leq b_j^* \leq M_j$. The search space consists only of those **IRETS** which are competitive, i.e., where $M_j > 0$.

In order to possibly reduce the search space and thereby save computer running time, we estimate whether or not each **IRET** (with $M_j > 0$) has a reasonable potential for market penetration before beginning the pattern search. To this end we estimate at what cost each technology would just begin to add new capacity. Let this “initial penetration” cost be κ_{zj} . We assume that, in the absence of cost diversity, if $c_j \geq \kappa_{zj}$, there would be no new capacity added, and if $c_j < \kappa_{zj}$, some new capacity would be added.

The **IRET** cost diversity is modeled as a normal (guassian) probability distribution with mean c_j and standard deviation

$$\sigma_j = [\Gamma(1 - 2/\gamma_j) - \Gamma^2(1 - 1/\gamma_j)]^{1/2} c_j.$$

We define the probability density function of the j -th cost to be $p_j(c)$. This cost probability allows negative pricing, but with extremely small and negligible probability. For $\gamma_j = -10$, the cost standard deviation is $0.1145c_j$ or about 11% of the nominal cost. If the nominal cost is 2.5 standard deviations or more greater than the initial penetration cost, we assume that the technology has no potential for competition (at the particular simulation time, not for all time) even with cost diversity; that is if $c_j - 2.5\sigma_j \geq \kappa_{zj}$, then the j -th **IRET** is removed from the search space and classified as noncompetitive. Setting this cutoff limit at 2.5 standard deviation ignores at most 6.62% of the potential penetration.

The values of the κ_{zj} are estimated by a numerical gradient. In order to succinctly and clearly explain how the gradient is computed we define the following special notation. Let the set $\alpha_j(\chi, x) = \{\xi_j\}$ consist of all J values of the set χ except the j -th one, and let the value of the j -th one be x . For example, suppose $J = 4$, and we have the values $\chi = \beta = \{b_1, b_2, b_3, b_4\}$. The set α_3 would have $\xi_1 = b_1$, $\xi_2 = b_2$, $\xi_3 = x$, and $\xi_4 = b_4$.

We repeat a previous result. The total system cost for candidate set β is

$$c = K(\beta) + \sum_j c_j b_j,$$

where $\beta = \{b_j\}$ for $0 \leq b_j \leq M_j$. For any fixed value of c_j , the minimum value of c is obtained where its partial derivatives with respect to the b_j are zero; i.e., the necessary condition that the b_j be optimum (minimize c) is where

$$\partial c / \partial b_j = 0 = c_j + \partial K / \partial b_j, \text{ or} \\ c_j = -\kappa_j,$$

where $\kappa_j = \partial K / \partial b_j$. Note that the equation above is valid for any nominal cost. Define a “small” step in the b_j dimension as δ_j . In the code we use $\delta_j = 0.02M_j$. The initial penetration for the j^{th} technology is estimated by computing

$$\kappa_{zj} = -[K(\alpha_j(\{0\}, \delta_j)) - K(\{0\})] / \delta_j.$$

The first term on the right side of the equation above is K evaluated with all new capacity candidates set to zero except the j -th one, which is set equal to δ_j , and the next term is k evaluated with all the b_j set to zero.

The pattern search now finds the optimal new capacity addition values, $\beta^* = \{b_j^*\}$, without cost diversity considered, of the technologies in the competitive search space. For each competitive technology one of three results are possible:

$$b_j^* = 0, 0 < b_j^* < M_j, \text{ or } b_j^* = M_j.$$

If the technologies are not competitive (not in the search space), then the optimal, cost diversified solution is $B_j = b_j^* = 0$, and they are not considered further in this simulation time.

An estimate of the effect of cost diversity on **IRET** new capacity additions is computed by defining a new capacity penetration function as a function of technology cost. The procedure is graphically described in Figure A.3. For each j this penetration function is evaluated with all new capacities except the j -th one set to their optimal solution, b_j^* . Call this function $\Phi_j(c)$. We assume that Φ is continuous, piecewise linear, with the derivative discontinuities at the values $c_{oj} > c_{mj} > c_{Mj}$. Let $0 < b_{mj} < M_j$ be the value of Φ at $c = c_{mj}$. We have

$$\Phi_j(c) = M_j, c \leq c_{Mj},$$

$$\Phi_j(c) = (c - c_{Mj})(b_{mj} - M_j) / (c_{mj} - c_{Mj}) + M_j, c_{Mj} < c \leq c_{mj},$$

$$\Phi_j(c) = -(c - c_{mj})b_{mj} / (c_{oj} - c_{mj}), c_{mj} < c \leq c_{oj}, \text{ and}$$

$$\Phi_j(c) = 0, c_{oj} < c.$$

Figure A-3. Iret Price Diversity

If $b_j = 0$ or $b_j = M_j$, then we set $b_{mj} = M_j/2$; otherwise we set $b_{mj} = b_j^*$. The cost points of the Φ_j function are estimated by a numerical gradient. We get

$$c_{oj} = -[K(\alpha_j(\beta^*, \delta_j)) - K(\alpha_j(\beta^*, 0))]/\delta_j,$$

$$c_{Mj} = -[K(\alpha_j(\beta^*, M_j)) - K(\alpha_j(\beta^*, M_j - \delta_j))]/\delta_j,$$

$$c_{mj} = c_j \text{ if } b_{mj} = b_j^*$$

$$c_{mj} = -[K(\alpha_j(\beta^*, b_{mj} + \delta_j)) - K(\alpha_j(\beta^*, b_{mj}))]/\delta_j, \text{ if } b_{mj} \neq b_j^*$$

The j -th **IRET** optimal new capacity addition adjusted for cost diversity is the convolution of Φ_j and the probability density function of the j -th cost,

$$B_j = \int_{-\infty}^{\infty} \Phi_j(c) p_j(c) dc,$$

see **Figure A.3**. This integral is easily evaluated in closed form [Gradshteyn and Ryzhik, 1965]. The B_j are the new capacity additions for the **IRETs** and the associated **DT** new capacity additions are computed from $B_i = \theta(\{B_j\})$ as described in section **A.3a**.

FORTTRAN COMMON Arrays and Symbol Table

Communications between the utility module and the energy production and capacity expansion modules is through FORTRAN labeled COMMON arrays. The convention is maintained throughout that symbols beginning with I through N (inclusive) are INTEGER *4, and all other variables are REAL *4. There are some REAL *8 variables, but they are internal to the module.

There are two kinds of technologies represented in the code. Symbols starting with or containing the letters “**RE**” are associated with **IRET** technologies. Storage is in the **RE** class. All other energy technologies are considered to be “conventional” in that they are essentially dispatchable. This second group, **DT** technologies, contains all fossil energy sources as well as renewable sources such as hydro, biomass, and geothermal. These technologies contain the letters “**CV**” in their symbols. In any particular year some of the competing **DTs** may or may not be available for purchase for various reasons.

Subroutine calls

The routine which computes energy production at the current problem time is called by

CALL CUDISP (X),

where X is an array of dimension at least NLDC and contains the NLDC values of the current demand table,)NLDC is the number of points in the load demand table, see below). The routine returns the IRET energy produced in array REEN, and the DT energy produced in array CVEN.

The capacity expansion routines are called by

CALL CAPEXP (X, CSTSYS),

where X is an array of dimension at least NLDC and contains the NLDC values of future estimated demand table. The routine's output is the amount of IRET and DT to purchase, in arrays RETP and CVTP, respectively, and the amount of energy dispatched for the total future system, assuming all purchased assets will have come on-line, is in arrays REEN and CVEN. The system cost, CSTSYS, is the sum of capital costs of all new purchases plus the cost of operation for the total future system. By "purchase" of capacity we mean begin construction of new capacity.

PARAMETER Statements

Labeled COMMON maximum array sizes are determined by three PARAMETERS. If any of the array sizes are to be changed, all pertinent PARAMETER values must be modified and the module re-compiled. The PARAMETERS are:

MXNRE = Maximum number of **IRET** technologies.
MXNCV = Maximum number of **DT** technologies.
MSNLDC = The maximum number of values (less one) in the energy demand tables (current and predicted). Although these table entries may be in any time-of-year order, we will refer to them as the LDC.

LDC COMMON Arrays

COMMON /COMLDC/ NLDC, NLDC1, DELLDC, WKLDC(MXNLDC),
PINLDC(MXNLDC), ADJLDC(MXNLDC)

Tabular values of the current and predicted demand for each time step are passed through subroutine arguments. Once initiated, the number of entries must remain the same for all time steps.

The entries may be in any time-of-year order (exception for storage, see below), but the order must be consistent with the time-of-year order of the IRET supply tables (RESUP). If there are NLDC entries, then it is assumed that each entry specifies demand for 1/NLDC part of the year.

NLDC = Number of entries in the current and future energy demand tables, $6 \leq \text{NLDC} < \text{MXNLDC}$. The value of NLDC must be preset before the first call to the module and may not be changed. If storage is used, NLDC must be a multiple of NHSTOD, see below.

NLDC1 = NLDC + 1. This value must be preset before the first call to the module and may not be changed.

DELLDC = 1/NLDC. This value must be preset before the first call to the module and may not be changed.

WKLDC, ADJLDC, and PINLDC are work arrays used by the module.

RE COMMON Data Arrays

COMMON /COMREN/ NRE, RECC(MXNRE), REOC(MXNRE), REMP(MXNRE),
REPA(MXNRE), REFPA (MXNRE), REAVS (MXNRE), RETP(MXNRE),
REEN(MXNRE), RESUP(MXNLDC,MXNRE,2) RECST(MXNRE),
REPLOG(MXNRE), ISWSTO, STOEFF, STOMER, NHSTOD

NRE = The number of competing **IRETs**, $0 < \text{NRE} \leq \text{MXNRE}$.

RECC = Levelized annualized capital cost of **IRET**, \$/kW_y.

REOC = Levelized annualized operating cost of **IRET**, \$/kW_y.

REMP = Maximum annual amount of the **IRET** that can be purchased, kW.
If REMP (j) is zero at any time, then the j-th **IRET** is not a candidate for capacity expansion at that time.

REPA = Amount of existing, on-line **IRET** physical assets, kW.

REFPA = Amount of **IRET** that will be on-line at the future time horizon of the capacity expansion, excluding new capacity additions suggested by the expansion routine, kW.

RETP = **IRET** new capacity additions, kW.

REAVS = Average capacity utilization factor of the future **IRET**. This quantity is given by

$$\text{REAVS}(j) = \sum \max [0, \text{RESUP}(i,j,2)]/\text{NLDC},$$

where the sum is over i.

REEN = Energy produced by the **IRET**, kW_y. For current dispatching REEN is the energy currently produced by REPA. For capacity expansion, REEN is the energy produced at the time horizon by the **IRET**, where it is assumed that

the future total on-line capacity of the **IRET** is REFPA + RETP.

RESUP = RE supply tables, nondim. RESUP(t,j,k) is the supply value for the j-th **IRET** at the t-th time, where the time order of RESUP for all **IRETs** must correspond to the time order in the given LDC tables. The k subscript refers to the time at which the supply is available. When calling CUDISP, k = 1 is the supply for the current problem time, and applies to REPA (k = 2 is not used). When calling CAPEXP, k = 1 is the supply is made since the best solar and wind sites tend to be used up as these technologies penetrate the market. If the j-th **IRET** has current on-line capacity REPA (j), then its energy output is

$$REEN(j) = REPA(j) * \sum RESUP(t,j,1) / NLDC,$$

summed over t. The energy output of the j-th RE at future time (assuming that all new capacity additions have come on-line) is

$$REEN(j) = [REFPA(j) * \sum RESUP(t,j,1) + RETP(j) * \sum RESUP(t,j,2)] / NLDC$$

sum over t.

For storage, RESUP is computed internally, and need not be inputted. Also, REEN is negative.

RECST = An internal work array.

REPLOG = Logit parameter for RE cost diversity, set to -10.

ISWSTO = Storage indicator. Only one **IRET** may be storage. If there is no storage, set SWSTO to zero, otherwise it is the index of the storage technology in the RE data set.

STOEFF = Storage efficiency, $0 < STOEFF < 1$.

STOMER = Storage maximum energy ratio, $0 < STOMER < 0.5$. This quantity specifies the maximum positive energy produced by storage. The upper bound of .5 is due to the fact that if storage is to provide energy to the system for some period of time, it must spend at least that much time recharging itself from the system. Storage is assumed to cycle diurnally.

NHSTOD = The number of “hours” in a storage “day.” It is assumed that storage charges and discharges energy on a diurnal cycle. If the input LDC is hourly, then NHSTOD should be set to 24. It is required that NHSTOD be even and at least 2. If storage is used, it is necessary that the LDC input be ordered in daily groups; that is, the first 24, say, data points refer to some day, and the next 24 to another day, etc. The order of days is not important. Also, NLDC must be a multiple of NHSTOD.

If there is no storage, ISWSTO = 0, and STOEFF, STOMER, and NHSTOD are not used.

The quantities REAVS, RETP, and REEN are output from the module, all other quantities are

input or work arrays.

CV COMMON Data Arrays

COMMON /COMCVT/ NCV, PLOGIT, SYSLOL, CVCC(MXNCV), CVOC(MXNCV),
CVFOR(MXMCV), CVPA(MXNCV), CVFPA(MXNCV), CVMCF(MXNCV),
KCVP(MXNCV), CVTP(MXNCV), CVEN(MXNCV), CVNS(MXNCV),
CVWT(MXNCV), GITNOR, IBEST

NCV = Number of **DT** technologies, $0 < \text{NCV} \leq \text{MXNCV}$.

PLOGIT = Parameter for the logit market penetration of the **DTs**. In accordance with the FOSSIL2 convention, set PLOGIT to -10.

SYSLOL = A factor concerning reserve margins for satisfying loss of load. SYSLOL should be preset to 0.25 by the user.

CVCC = Levelized annualized capital cost for the **DT**, \$/kW.

CVOC = Levelized annualized operating cost for the **DT**, when input to CAPEXP. When input to CUDISP, CVOC is the current operating cost, \$/kW.

CVFOR = Complement of the forced outage rate of the **DT**; that is, if the forced outage rate for the j-th **DT** is 10%, CVFOR(j) = .90.

CVPA = Current **DT** on-line capacity, kW.

CVFPA = Future on-line capacity, excluding new capacity additions, kW.

CVMCF = Maximum **DT** capacity utilization factor, ignoring forced outages, also referred to as the scheduled availability.

KCVP = Indicator of **DT** status. If KCVP(j) = 1, the j-th **DT** may be currently purchased; if KCVP(j) = 0, the j-th **DT** may not be currently purchased. At least one **DT** must be capable of being purchased at every time.

CVTP = **DT** new capacity additions, kW.

CVEN = Energy produced by the **DT**, kW. For current dispatching CVEN is the energy dispatched by the CVPA. For capacity expansion, CVEN is the energy produced at the time horizon by the **DT**, where it is assumed that the future total on-line capacity of the **DT** is CVFPA + CVTP.

CVNS = The nominal maximum power generating size of each individual unit of the j-th CVC technology. This array is used only under the Booth-Baleriaux cumulate option (INBC = 1), and may be ignored if the “integration” method (INBC = 0) is used.

CVWT, GITNOR, IBEST are work arrays used internally by the module.

The quantities CVTP and CVEN are output from the module, all other quantities are input or internal work arrays.

OPTIONS COMMON

COMMON /COMOPT/ TIME, PTIME, IPR, IPCT, IOM, INBC, INDD, GADER

The only element in this common that need be set by the casual user is TIME, which is the current problem time in years. The other quantities have to do with various internal options in the code.

TIME = Current problem time in years.
 PTIME = A switch used in code checkout. Set to zero.
 IPR = Another checkout switch. Set to zero.
 IPCT = Another checkout switch. Set to zero.
 IOM = CV expansion option. Set to zero.
 INBC = Option to use the "integration" method (INBC = 0) or the Booth-Baleriaux method with cumulants (INBC = 1). Set to zero.
 INDD = Option to use RE price diversity (INDD= 0) or not to use RE price diversity (INDD = 1). Set to zero.
 GADER = A parameter having to do with RE search space smoothness. Set to 0.03.

Initialization

Once the value of NLDC is established, but before CUDISP or CAPEXP are called, the user should initialize the following variables. The quantities with an asterisk are suggested, but not required, values.

NLDC1 = NLDC + 1	DELLDC = 1./REAL(NLDC)	PLOGIT = -10.*
SYSL0L = 0.25*	REPLOG(...) = -10.*	PGTIME = 0
IPR = 0	IPCT = 0	IOM = 0
INBC = 0	INDD = 0.	GADER = 0.03*

These quantities, plus NRE, NVC, ISWSTO and NHSTOD, should not be changed once a simulation is started!

FORTTRAN/Math Symbol Table

This table correlates the FORTRAN symbols with the mathematical symbols used in the exposition of the algorithms.

<u>FORTTRAN Symbol</u>	<u>Math Symbol</u>
NLDC	T
X(t)	L_t
NRE	J
RECC(j)	C_{cj}
REOC(j)	C_{oj}
REMP(j)	M_j
REPA(j)	P_j

REFPA(j)	F_j
RETP(j)	B_j
REEN(j)	E_j
RESUP(t,j,1)	S_{tj1}
RESUP(t,j,2)	S_{tj2}
REPLOG(j)	γ_j
STOEFF	e_{ps}
STOMER	r_{ps}
MHSTOD	H
NCV	I
PLOGIT	γ
SYSLOL	r_m
CVCC(i)	C_{ci}
CVOC(i)	C_{oi}
CVFOR(i)	f_i
CVPA(i)	P_i
CVFPA(i)	F_i
CVMCF(i)	S_i
KCVP(i)	k_i
CVTP(i)	B_i
CVEN(i)	E_i

APPENDIX B. Investigation of Utility Capacity Expansion Model Concerns

Date: March 16, 1992

To: Joe Galdo, DOE/CE/OUT

From: Mike Edenburn and Gene Aronson, Sandia/6601

Subject: Investigation of Utility Capacity Expansion Model Concerns

Summary

At our January 30 quarterly review, Jack Cadogan expressed several concerns related to the efficacy of our model. We felt that they were legitimate concerns which will be shared by many future model reviewers, and we have spent some time addressing them. We addressed the concerns in the context of our objective which is to construct a simplified model for studying the effects of alternative policy strategies on renewable energy technology penetration into the utility market. The model is not intended for use in detailed utility capacity expansion planning.

The first main concern was related to treating averaged intermittent source production as a negative load. This concern was shared by Narayan Rau at an earlier meeting with NREL. Jack stated that using a deterministic profile will over-estimate an intermittent source's capacity value, and he suggested reading several documents including some by Grubb, Fegan, and Percival. The documents cautioned that treating averaged intermittent production as a negative load will over-value intermittent capacity. Grubb suggested that if intermittent source production is averaged and treated as a negative load, capacity valuation will be accurate for small penetrations but not for large penetrations. We performed analyses which verified Jack's concern and concluded that capacity valuation is accurate up to about 5% penetration but can be roughly 20% high for 10% penetration and even higher for 20% penetration when one average production day is used to represent an entire month. Although over-valuation is significant for large penetration, results are more accurate than assuming no or full capacity credit, and they may be acceptable, particularly if penetration does not exceed 10%. Errors arise because averaging intermittent production does not adequately capture its probabilistic nature. Errors can be reduced by using more data or by using a probabilistic analysis. We are examining ways to capture the probabilistic nature of intermittent production without significantly increasing computational burden, but we expect that there will be a tradeoff between accuracy and computational burden.

The second main concern was related to production costing (dispatching). This concern was also shared by Narayan Rau. It was addressed in an earlier memo (Comparison of Sandia's Utility Capacity expansion and Dispatching Model to More Detailed Methods, dated November 26, 1991, from Mike Edenburn to Distribution). We revisited the issue, but this time we included scheduled outages. We compared three analyses: 1) a probabilistic analysis with seasonal, scheduled outages; 2) a probabilistic analysis with a scheduled outage approximation suggested by Peter Lilienthal from NREL; and 3) a load duration curve integration method with a scheduled outage approximation (the method our model uses). Method #1 is the more rigorous of the three and is used as a standard. Both of the approximate methods are in good agreement with method #1 (the values of displaced energy agree within 5%).

The third main concern was directed at our method for optimizing dispatchable capacity expansion. This is the method where we assume that all new dispatchable capacity is added at a capacity factor represented by the gap between two existing technologies. (Existing technologies are arranged in merit order on a load duration plot.) The allocation of new capacity is determined by a logit apportionment and the capacity gap location which results in the lowest cost is selected.

Part of the concern with this method derives from our failure to provide a clear explanation, and we have included further explanation in this memo. The rest of the concern is that the method gives "noisy" results. A particular technology may make a relatively large penetration in one year followed by very small penetrations in subsequent years. While our method does not give a true optimum expansion in any single year, it tracks the optimum from a more detailed method very well over several years. We have modified the method, and the modification tends to smooth results. In addition to adding new assets all in one place between existing adjacent technologies, we also divide new capacity equally between all pairs of existing adjacent technologies. New capacity share for each location is determined by a logit apportionment applied for the capacity factor at each location. The total cost for the equally distributed addition is competed with costs for the "all in one place" additions, and the minimum cost option it is selected. As before, the method does not provide a true optimum expansion in any single year, but with the new addition, it tracks the more detailed method closer and more smoothly than before.

Each of the three concerns will be discussed in more detail.

Objective Function

To begin a discussion of the concerns, we will try to put them into perspective by describing the model's quantitative objective:

Find the mix of competing technologies, both intermittent and dispatchable, which must be added to a utility system to satisfy a projected electrical load at minimum levelized annual cost.

Levelized annual cost is described mathematically by Equation 1.

$$T = \sum [C_{ci}B_i + C_{oi}E_i(B_i + F_i)] \quad (B-1)$$

T is total future (after planning horizon) levelized annual cost,
 C_{ci} is levelized annual capital cost (\$/kW-Yr) of the ith technology,
 C_{oi} is levelized annual operating cost (\$/kWh) of the ith technology,
 E_i is annual energy generated (kWh/kW-Yr) by the ith technology,
 B_i is the new capacity increment (kW) of the ith technology, and
 F_i is the existing and under construction capacity (kW) of technology i
that will be on line at the planning horizon time.

This is the model's objective function which we want to minimize while satisfying the utility system's load requirements. The total future system cost is the sum of levelized capital cost for new capacity and levelized operating cost for all capacity. The model's objective is to select the values of B_i which minimize T. To select correct values of B_i we require accurate values for capital and operating cost, accurate values for E_i , and a process which identifies the optimum B_i 's.

Our model uses a simplified production costing (dispatching) algorithm to compute values for E_i . The dispatching algorithm's accuracy is the subject of the second concern expressed above. Also, treating intermittent production as a negative load (the first concern expressed above) is important to production costing accuracy because negative loads partially determine the system's load duration curve, and an accurate load duration curve is required for accurate production costing.

Finding the optimum set of B_i 's is conceptually simple but not computationally simple. We have sophisticated algorithms which can find the B_i 's, but they are too cumbersome and time consuming for the simplified model we are trying to develop. The algorithm we use is "near-optimal" and follows optimal results with acceptable agreement. The accuracy of our "near-optimal" algorithm is the central issue in the third concern expressed above.

Equation 1 is subject to a constraint as defined by Equation 2.

$$\sum (B_{id} + F_{id}) = P^* \quad (B-2)$$

B_{id} and F_{id} refer to new and existing dispatchable capacity. This equation requires that the sum of dispatchable capacities must be equal to total dispatchable capacity P^* which is the peak net load plus a reserve margin. The required reserve margin value depends on meeting a prescribed loss of load probability or on meeting a prescribed unserved energy. Reserve margin plays an important role relative to treating intermittent production as a negative load because the treatment of negative loads affects the system's net peak load and the shape of its load duration curve.

Understanding the importance of the dispatching algorithm and the optimization algorithm will help keep the following discussion in perspective.

Treating Intermittent Production as Negative Loads

In our model, we have been representing intermittent production by one "average" day per month.

To get production for each hour of the "average" day, we average production for each hour over the month. The hourly data used to find the monthly average are themselves an average of ten minute or smaller intervals over the hour. Thus, our monthly average for each hour is an average of an average. Intermittent production is treated as a negative load; that is, production is subtracted from load to get a net load. By treating intermittent production as a negative load we are, in effect, assuming that the intermittent source has a firm capacity equal to its average production during each hour. Production values below the average will give firm capacity values below average, and production values above the average will give firm capacity values above average. Below average values are weighted more heavily than above average values in a loss of load probability or unserved energy analysis; thus, using the average over-predicts firm capacity value. One might conclude that, since we are using averages of averages, the error is being compounded and that we can never achieve accuracy until we use instantaneous data over an infinite number of years. Fortunately, this is not true. If, for each load value, the statistical distribution of production data is representative of the distribution of all production data corresponding to that load value, our results will be accurate. In general, there are many hours during a year which have the same or nearly the same load and these loads will have a range of associated intermittent production values. If the range of production values matches the "true" distribution, then results will be accurate. How much data do we need for reasonable accuracy? We assume that a year's worth of hourly data gives a sufficient range of production values for each load value to give reasonably accurate results. We believe that this is a good assumption, but we do not have the resources available at present to validate it. We will use this assumption in the analyses that follow.

To quantify the effect of averaging intermittent production data, we considered a PG&E hourly annual load profile and an hourly wind production profile based on Fresno TMY data. The magnitudes of both profiles were altered to fit our analyses, but time dependence was not altered. We considered a utility composed of the following generation units.

<u>Type</u>	<u>Number</u>	<u>Capacity</u>	<u>Availability</u>
Nuclear	1	850 MW	.908
Coal	8	250 MW	.963
Combined Cycle	8	150 MW	.945
Gas Turbine	9	50 MW	.965

These units represent the US proportion of thermal units (EIA's Electric Power Annual, 1989) with availabilities (due to forced outages) taken from EPRI's Technical Assessment Guide.

Using a probabilistic production model, we computed the firm capacity which results in the same unserved energy as a rated wind capacity. We did this for two cases. The first case used hourly load and hourly wind data for a year. The second case used hourly load data and monthly average day wind data. Results are shown in the following table.

<u>Peak Load MW</u>	<u>Rated Wind Capacity MW</u>	<u>Equivalent Firm Capacity MW Hourly Annual</u>	<u>Equivalent Firm Capacity MW Ave. Day per Month</u>
3900	100	55.4	54.3
	500	208	254
	1000	287	457
4500	1000	331	474

Using average day-per-month wind data results in roughly the same capacity value as using hourly annual wind data for a 100 MW (roughly 2% of total capacity) wind penetration. At 500 MW penetration (10% of total capacity) the error is 22% and at 1000 MW (18% of total capacity) the error is 59%. Increasing the peak load (from 3900 to 4500 MW) reduces the error, but it does not eliminate it. This analysis verifies that using monthly average intermittent production values as negative loads overestimates capacity value for large penetrations.

The best way to visualize the statistical accuracy of using average intermittent production values is through the net load duration curve (the load duration curve formed after intermittent production values have been subtracted from loads). If two load duration curves are the same, loss of load probability, unserved energy, and production costing analyses will give the same results. Using average intermittent production values will tend to flatten the curve while using a distribution of production values will tend to make it steeper at the beginning and end. Figure 1 shows a load duration curve for a peak load of 3900 MW and a rated wind capacity of 1000 MW for hourly annual load and wind data and for hourly annual load and monthly average day wind data. The differences in shape between the two curves account for the differences in capacity value shown in the above table.

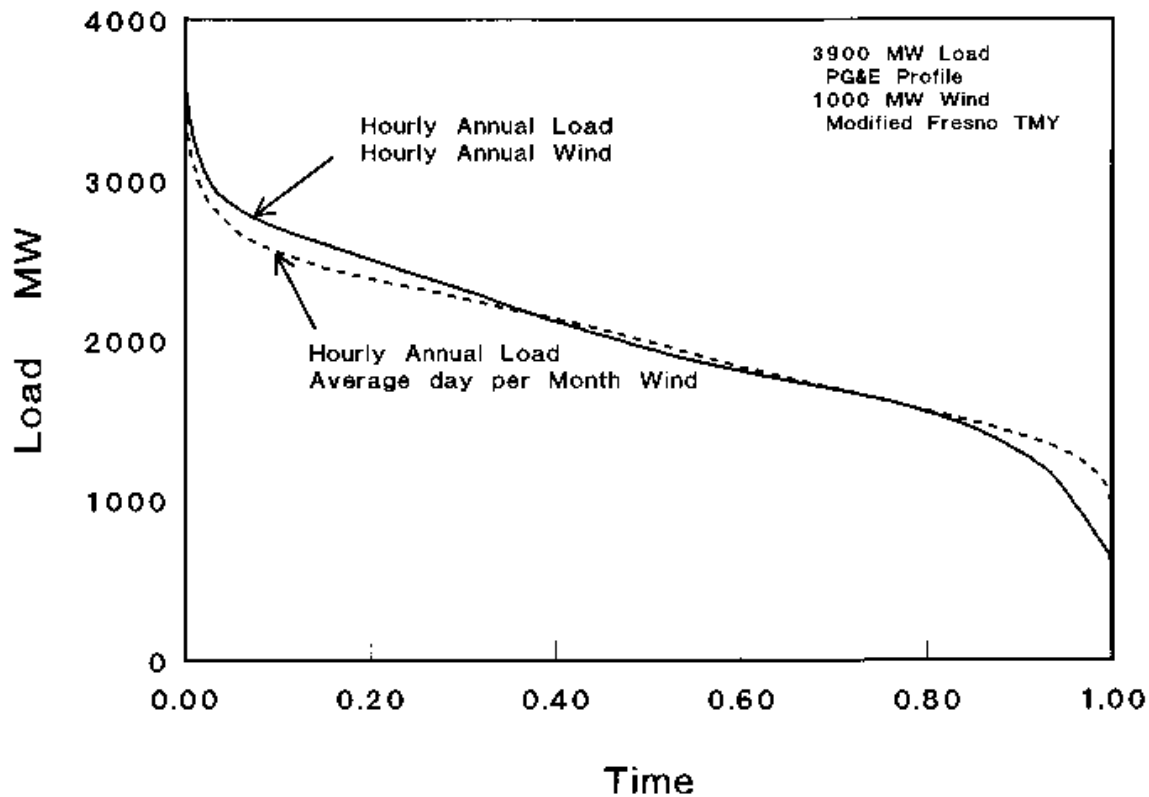


Figure B-1. Load Duration Curve Comparison

We do not want to use hourly data in our model because of the computer time required, so we have examined an alternative way to treat intermittent production. Instead of using an average day per month, we tried three days per month. The first day uses the average wind production for the highest third of the month's data at each hour. The second day uses the average of the middle third, and the third day uses the average of the lower third. This introduces a intermittent production distribution (albeit a crude one) into the model. It captures low, medium, and high values of intermittent production for each hour. We also formed three load days for each month. One represents a peak load day; another represents a minimum load day; and the third represents an intermediate load day. The three load days and three wind production days are used in all combinations to give nine days per month of net load data. The resulting annual load duration curve is compared to the one derived using hourly annual data in Figure 2. The match is quite good.

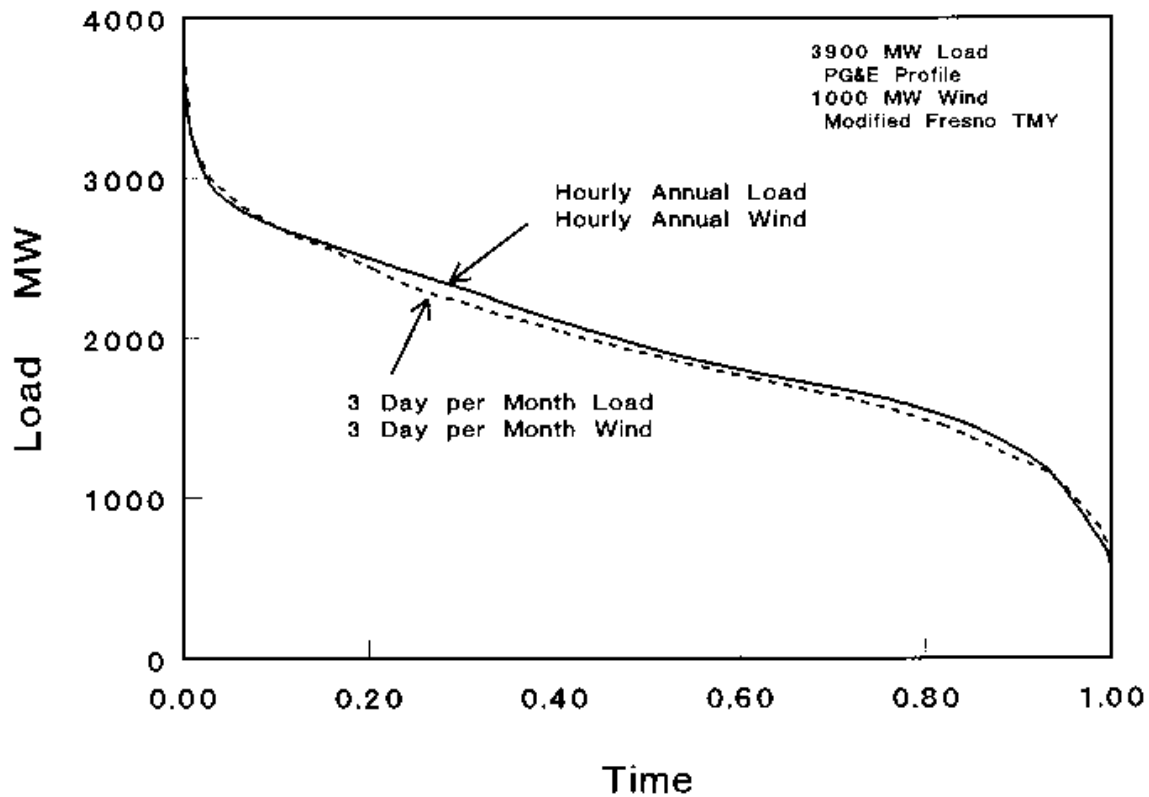


Figure B-2. Load Duration Curve Comparison

Using the three day per month data in the equivalent firm capacity analysis gives the following results.

Peak Load MW	Rated Wind Capacity MW	Equivalent Firm Capacity MW Hourly Annual	Equivalent Firm Capacity MW Ave. Day per Month	Equivalent Firm Capacity MW Three Day Per Month
3900	100	55.4	54.3	58.5
	500	208	254	233
	1000	287	457	330
4500	1000	331	474	393

The three day per month data results in much more accurate capacity value estimates than the one day per month data. The error for 10% penetration is 12% instead of 20%, and the error for 20% penetration is in the 15-20% range instead of 40-60%. We are evaluating using the three day per month instead of the one day per month data in our model. Using more data will require more computation time.

Production Costing (Dispatching)

The production costing (dispatching) algorithm is used to compute the energy generated (values of E_i in Equation 1) by each type of generation technology during a year. The algorithm inherently accounts for displaced energy generation when an intermittent source is added to the system and is important in determining the value of an intermittent source. Our simplified dispatching algorithm simply integrates the net load duration curve to find the annual energy generated by each type of unit. It does an approximate accounting of scheduled outages. We also modeled a probabilistic production method (Booth-Baleriaux). The probabilistic method does not inherently consider scheduled outages because they are not random. Scheduled outages were incorporated by dividing the year into time blocks and scheduling outages for maintenance within each block. The probabilistic method is applied to each time block individually.

To quantify the differences between our simple load duration curve integration method and the probabilistic method using time blocks for scheduled outages, we applied the two methods to a test case. The test case consisted of the dispatchable generation system described in the table below, a 3900 MW peak load with PG&E's 1989 profile, and adjusted Fresno TMY data.

<u>Type</u>	<u>Number</u>	<u>Capacity</u>	<u>Availability (Random)</u>	<u>Scheduled Outage</u>
Nuclear	1	850 MW	.908	.252
Coal	8	250 MW	.963	.062
Combined Cycle	8	150 MW	.945	.062
Gas Turbine	9	50 MW	.965	.055

This generation system's scheduled outages were chosen so that units could be serviced in exact quarterly time blocks. They are not real scheduled outages.

The probabilistic method with scheduled outage time blocks assumed the following maintenance schedule:

- nuclear plant down in the fall,
- one coal plant at a time down in winter and spring,
- one combined cycle plant at a time down in fall and winter, and
- one gas turbine plant at a time down in winter and spring.

This schedule balanced the loss of load probability among the seasons and minimized annual loss of load probability. Our load duration curve integration method accounted for scheduled outages by comparing the energy computed by integration with the maximum possible energy from each type of plant (the product of rated power, forced outage availability, and scheduled outage availability). If the integrated energy exceeds maximum energy, the plant is derated to make the two energy values balance. We also considered a third dispatching method based on one suggested by Peter Lilienthal at NREL. It uses the probabilistic method but incorporates the same scheduled outage accounting method as our integration method. That is, it derates a plant if

necessary to ensure that its energy generation limit is not exceeded. Derating is equivalent to assuming that scheduled outages are random, like forced outages. To compare the three methods, we computed the energy displaced from each dispatchable plant when 500 MW of wind or photovoltaic capacity was added to the system. Energy displacement is found by exercising the dispatching algorithm with and without the intermittent source. Results from the two runs are subtracted to find energy displacement.

Displaced Energy in TWh					
	<u>Nuclear</u>	<u>Coal</u>	<u>Comb Cyc</u>	<u>Gas Turb</u>	<u>Value M\$</u>
500 MW Wind System					
Probabil/Seasonal	0.	1.09	.75	.035	54.7
Integration/Derating	0.	1.17	.71	.006	52.7
Probabil/Derating	0.	1.21	.64	.035	52.6
500 MW PV System					
Probabil/Seasonal	0.	.37	.57	.026	31.7
Integration/Derating	0.	.39	.58	.006	31.0
Probabil/Derating	0.	.49	.45	.032	29.8

The value of displaced energy was found using .021 \$/kWh for coal operating cost, .039 \$/kWh for combined cycle, and .072 \$/kWh for gas turbine (derived from EPRI's TAG economic parameters). Our integration method underestimates energy displacement from gas turbines, but its value computation is fairly accurate. The probabilistic method with derating for scheduled outages is also fairly accurate and it makes a better estimate of gas turbine energy displacement, but it requires greater computing time.

The object of the dispatching algorithm is to accurately estimate the value of energy displaced by intermittent sources. Our simple integration method does an adequate job, but we must keep in mind that it underestimates energy displacement from peaking turbines.

Capacity Expansion Optimization

Optimization requires finding the technology mix for new capacity which minimizes levelized annual cost subject to a reserve margin constraint. The optimization our model employs is an approximation from three perspectives: 1) as discussed above, the operating costs our model calculates are approximate; 2) our reserve margin estimate is approximate; and 3) the optimization process itself seeks a near optimum, not a true optimum. The following describes our near optimization process.

We search to find the combination of intermittent renewable energy technology (IRET), storage, and dispatchable new capacity which minimizes cost. To start the process, we select an IRET-storage set. That is, we select a new capacity value for wind, a value for PV, a value for solar thermal, and a value for storage (storage may require two values: one for energy and one for

power). Using this IRET-storage new capacity set, we compute a net load duration curve. Next, we find a near optimum set of new dispatchable technology capacities which satisfies (provides the required energy and power) the net load duration curve at near minimum cost. We repeat this process for different IRET-storage sets in a patterned search until we locate the IRET-storage set which minimizes levelized annual cost for the entire system. Since each IRET-storage set has an "attached" minimum cost dispatchable set, finding the minimum cost IRET-storage set minimizes cost for the entire system.

The method we use to find a near optimum (near minimum cost) new dispatchable capacity set is the subject of the third main concern expressed above. In Figure 3 we show a net load duration curve with existing dispatchable technologies applied in merit order. Merit order means that the lowest operating cost technology is applied at the bottom where the most energy is produced followed by the next least expensive operating cost technology and so on until the last technology applied has the highest operating cost and provides the least energy. Peak load exceeds total existing capacity, and we call the difference a capacity gap which must be filled by new capacity. A true optimization will distribute the capacity gap among the different technologies in a way that minimizes system levelized annual cost. Sherali of VPI has a method for optimizing new capacity. His method will find the true optimum given that production costing (dispatching) is approximated using the load duration curve integration method. In other words, it is an exact optimization to an approximate problem. We do not use Sherali's method because it has a high computational burden and it does not consider cost diversity. Our method follows the following procedure. First, we assume that the entire capacity gap is inserted between each pair of adjacent existing technologies which are arranged in merit order. Each insertion location has a capacity factor associated with it. We compute the levelized annual cost for each competing technology at this capacity factor. (Levelized operating cost is a linear function of capacity factor.) Then, we use the computed costs in a logit apportionment to determine the capacity share of each competing technology. If the capacity gap is inserted between base and intermediate technologies, then the capacity factor will be high and base and intermediate plants will be favored in the logit apportionment because their levelized annualized costs will be relatively low, but every competing technology will receive a share of the capacity gap. If the gap is inserted between intermediate and peaking technologies, the capacity factor will be low, and intermediate and peaking technologies will be favored.

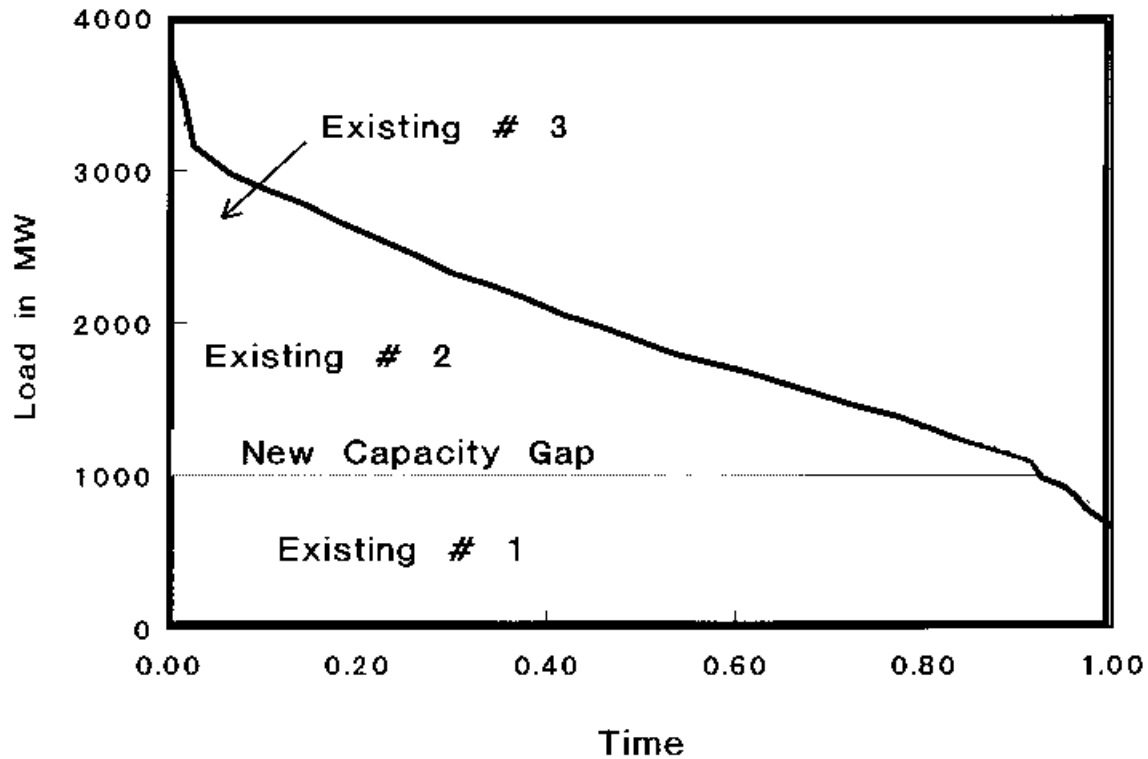


Figure B3. Capacity Gap Method

The number of insertion options is equal to the number of existing technologies minus one because there are that many pairs of adjacent existing technologies between which the capacity gap can be inserted. For each option, we compute the share each technology will get of new capacity. We have added a new option to the model since our meeting. We divide the capacity gap up equally between each pair of existing technologies and use a logit apportionment to determine the share of new capacity each technology gets.

We merit order new and existing technologies for each option and use our dispatching algorithm to compute total levelized operating cost and add levelized capital cost to compute the total cost for each option. The option with the lowest cost is selected. Keep in mind that we always add at least some of each technology. If the system is short of base capacity, then the option which inserts the capacity gap between existing base and intermediate will probably be selected. If the system is pretty well balanced, then the equally distributed capacity gap will probably be selected. This method does not select an optimum expansion in any given year, but over time the expansion is near optimum. To illustrate this, we have compared our expansion method to Sherali's method. Our method includes price diversity through the logit apportionment. We incorporate price diversity into Sherali's method by using a cost distribution for each technology and a Monte Carlo assignment of cost. The final result is the average of all the Monte Carlo results at each time. Figures 4, 5, and 6 compare results for the two methods for a system where load grows by 2% each year.

Base Capacity

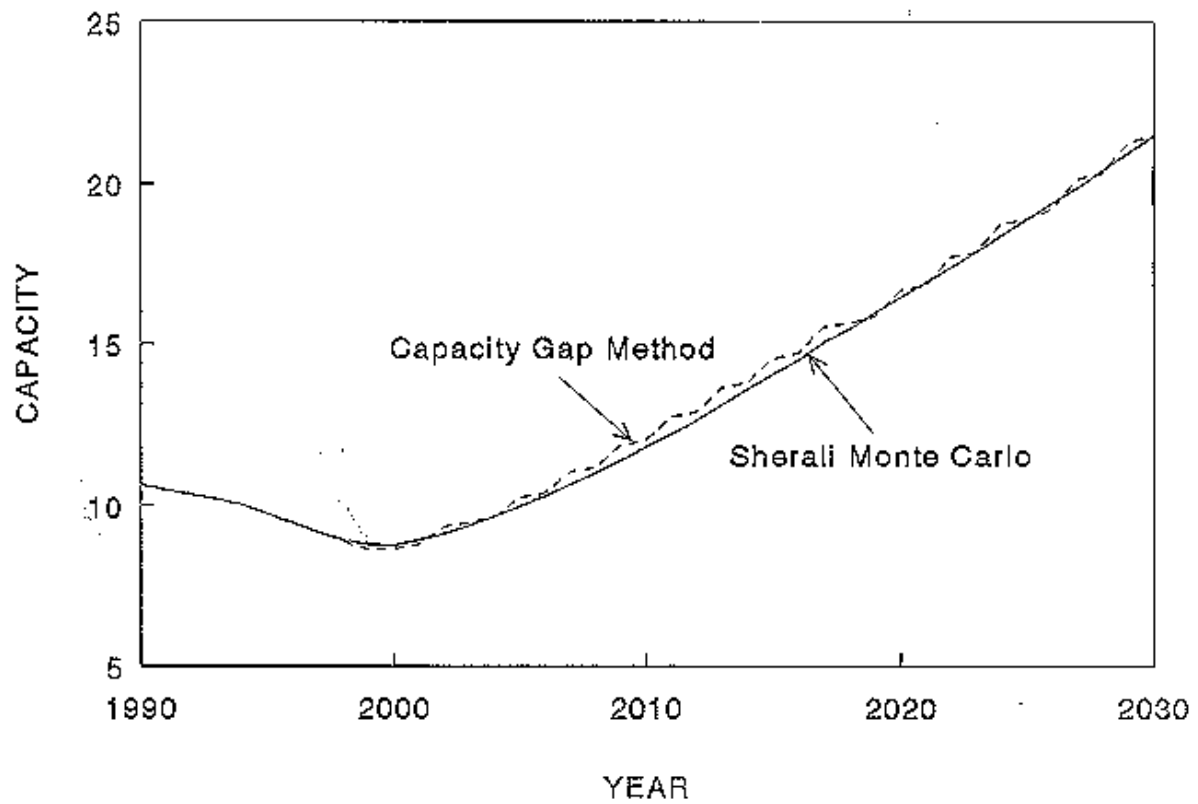


Figure B-4. Base Assets (Nuclear + Coal)

Intermediate Capacity

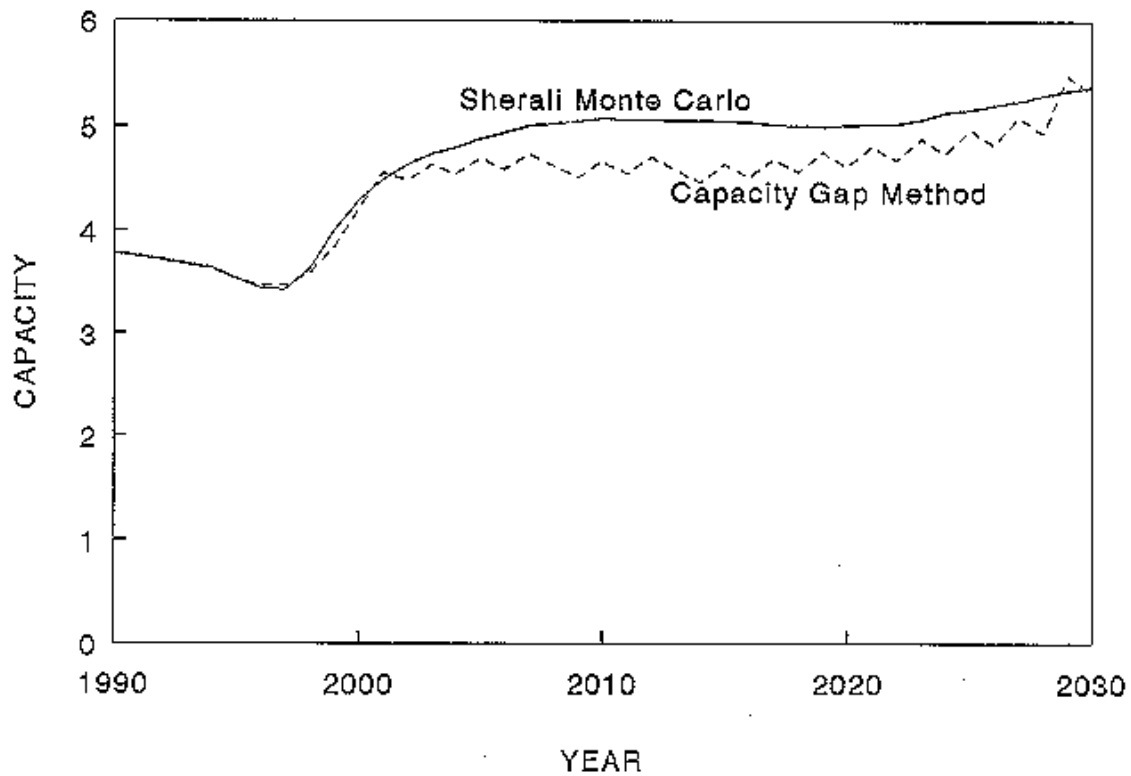


Figure B-5. Intermediate Assets (Combined Cycle)

Peak Capacity

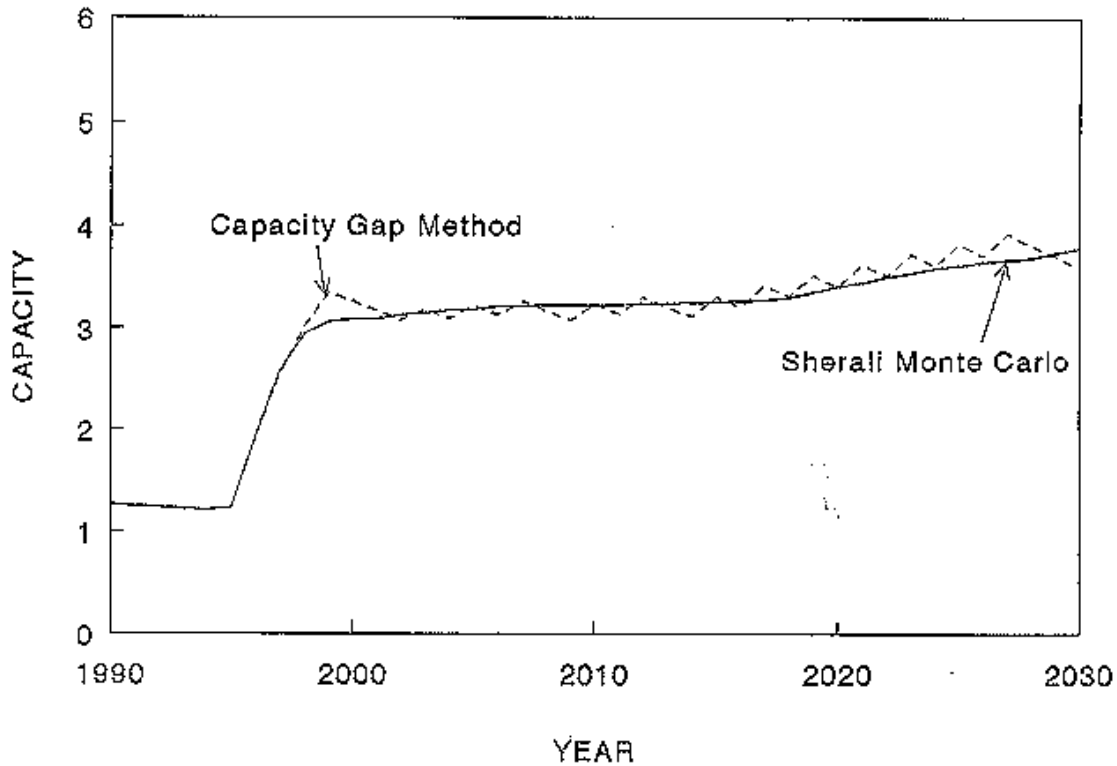


Figure B-6. Peak Assets (Gas Turbines)

Our capacity gap expansion method tracks Sherali's true optimization method (with Monte Carlo) very well. Both of these methods use our load duration curve integration method to compute levelized operating cost which is an approximation to true operating cost. Because of this, neither method gives a true optimization, but we have shown that our load duration curve integration method makes a reasonably accurate estimate of operating cost. From this, we conclude that our optimization method combined with our dispatching method will make reasonable expansion estimates. We have neglected an important element in this logic. We have not discussed reserve margin. An approximate method for estimating reserve margin is planned, but we have not yet evaluated its impact on proper valuation of IRET's.

Conclusion

We have addressed the main concerns raised at our quarterly review meeting. In addressing them we have identified areas where improvements can be made. In some cases the improvements have been made. We conclude that our approximations are reasonable for the type of model we are constructing. It is not a utility tool for planning capacity expansion. It is a model for projecting the effects various policy strategies will have on IRET penetration trends. We are planning to

have the model reviewed by people familiar with utility capacity expansion planning. The first review scheduled is with Neal Balu, EPRI's AGEAS project manager, in early April. We are in the process of getting an AGEAS test case from Leslie Buttorff at Stone and Webster and will use it to compare our model's results with those from AGEAS.

If you have any questions or suggestions about the work covered in this memo, please call us:
Mike Edenburn 845-8297 or Gene Aronson 844-4348.

APPENDIX C. Comparison of the Dispatchable Capacity Expansion Method with the Exact Sherali Method

For a given anticipated load demand curve, a given set of dispatchable technologies with associated annual levelized capital and operating costs, and set of existing, on-line capacities for each technology, the exact solution of the optimal expanded dispatchable technology configuration is found by a method devised by Sherali [Sherali, 1985], under the assumption that energy production is computed by the “integration” method, described in the main body of this report, and in Appendix A . By the optimal configuration we mean that configuration which minimizes the system life-cycle cost. The integration method of energy production and a comparison between it and the Booth-Baleriaux probabilistic method is found in the body of this report and in Appendix B. If there are no existing capacities, the solution is very simple, and given by the well-known “screening curve” method [Steiner, 1957].

Let the subscript i refer to the i -th technology in a system consisting of N technologies. Total system future life-cycle cost is given by

$$(C-1) \quad C = \sum C_{ci}B_i + C_{oi}E_i(B_i + F_i)$$

where the sum is on $i = 1, 2, \dots, N$, and

- C is the total future annualized cost, \$/yr).
- C_{ci} is the levelized annual capital cost (of the i -th technology), \$kW-yr.
- B_i is the **new** capacity addition, kW.
- C_{oi} is the levelized annual operating cost, \$/kWyr.
- E_i is the energy produced, kWyr.
- F_i is the future (derated) existing capacity, including capacity under construction that will be on-line at the future time, less retirements that will be in effect at that time, kW.

The Sherali method assumes that all capacities have been derated to account for forced and scheduled outages. The energy production is computed by “merit ordering” of the technologies, with the lowest operating cost technology dispatched first, the next-lowest second, etc., thus guaranteeing the minimal operating cost for the system. Therefore, we order the subscripts i by

$$(C-2) \quad C_{o1} \leq C_{o2} \leq \dots \leq C_{oN}.$$

Let the load demand curve be $\lambda(u)$, where λ is in kW and u is that part of the year in which the expected load will exceed $\lambda(u)$. The quantity u is also the capacity factor associated with the load $\lambda(u)$. The load is a monotonically non-increasing, positive function of u defined over the domain $0 \leq u \leq 1$, see Figure C-1. Since the capacities are already derated, the energy produced is

$$(C-3) \quad E_i = \int_{U_{i+1}}^{U_i} u(\lambda) d\lambda,$$

$$U_i = \sum_{\xi=1}^i B_\xi + F_\xi$$

Figure C-1. Load Demand and Merit Ordering

The function $u(\lambda)$ is the inverse load demand defined over the domain $[0, \lambda(0)]$. A constraint on the problem is that all demand must be satisfied, i.e.,

$$(C-4) \quad U_N \geq \lambda(0).$$

The exact solution, which finds the B_i so that C , equation (C-1), is minimized, given conditions in equations (C-2) through (C-4) was found by Sherali to involve a somewhat complicated mathematical programming problem described in the 1985 reference.

We coded the Sherali method and tested it against various configurations. In spite of having coded the method, we decided it was not appropriate for use in our capacity expansion module for three reasons:

1. It was quite complicated, although it did not generally use excessive computer time.
2. The preset derating requirements clouded the interplay between forced and scheduled outages.
3. It did not allow cost diversity among the technologies.

The third reason was the most compelling, since we feel cost diversity is an important feature of the module.

In lieu of using the Sherali method for capacity expansion, we attempted to devise a method which tended to emulate Sherali's solutions for similar conditions, resulting in the heuristic method described in Appendix A. Our heuristic method was compared against Sherali's method for a test case, whose results are shown in Figure C-2, C-3, and C-4. We used the "typical" initial load curve shown in figure C-1, and assumed a system of three technologies: "base," intermediate, and peak, with appropriate capital and accounting costs. We chose a set of initial capacities and a load growth of 2% per year. A simulation was run with each system, our heuristic solution and Sherali's exact solution, expanding over a 40 year period.

Since the Sherali method does not allow cost diversity, we simulated it by running the Sherali simulation as a 400-pass Monte Carlo, with capital and operating cost as independent random variables at each time step in each pass. The plotted results are the average capacities over all passes at each time step; that is, if $Y_i(t,j)$ is the total capacity of the i -th technology at the t -th time step of the j -th Monte Carlo run, the resultant capacity at the t -th time is

$$Y_i(t) = \sum Y_i(t,j)/400$$

where the sum is on j from 1 to 400.

Base Capacity

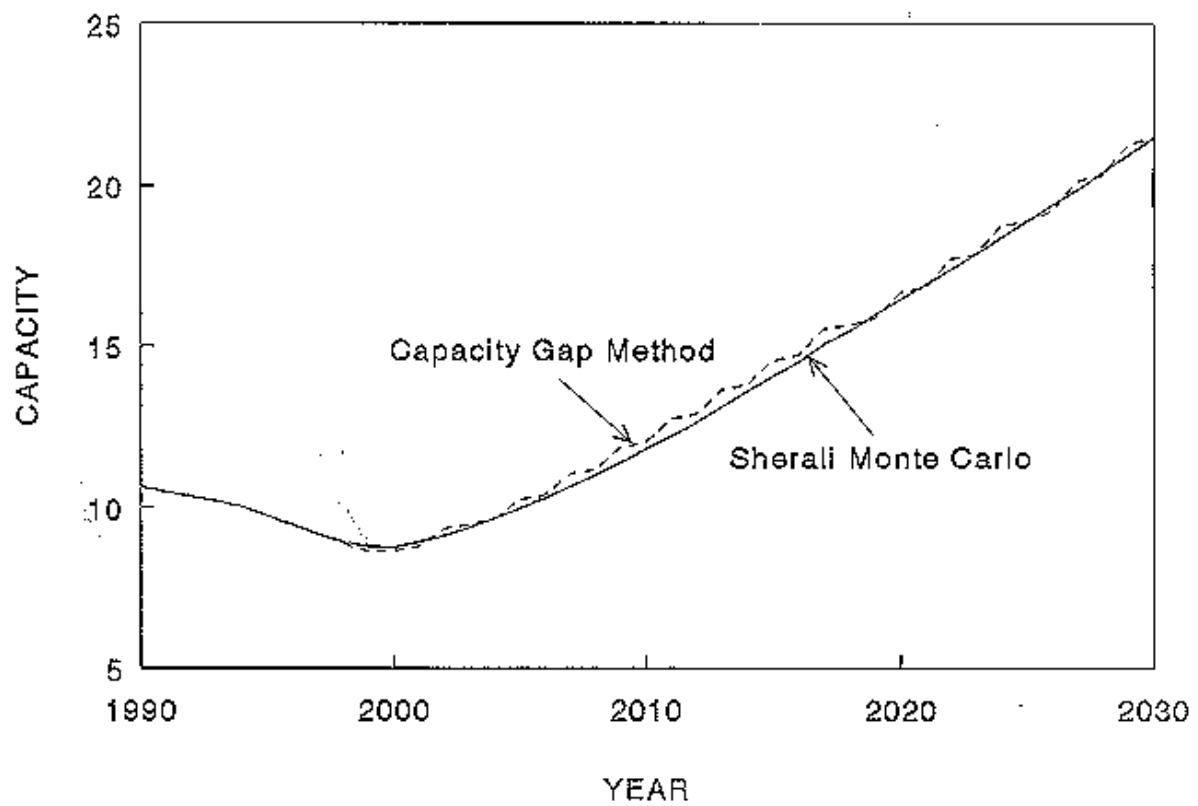


Figure C-2. Base Capacity

Intermediate Capacity

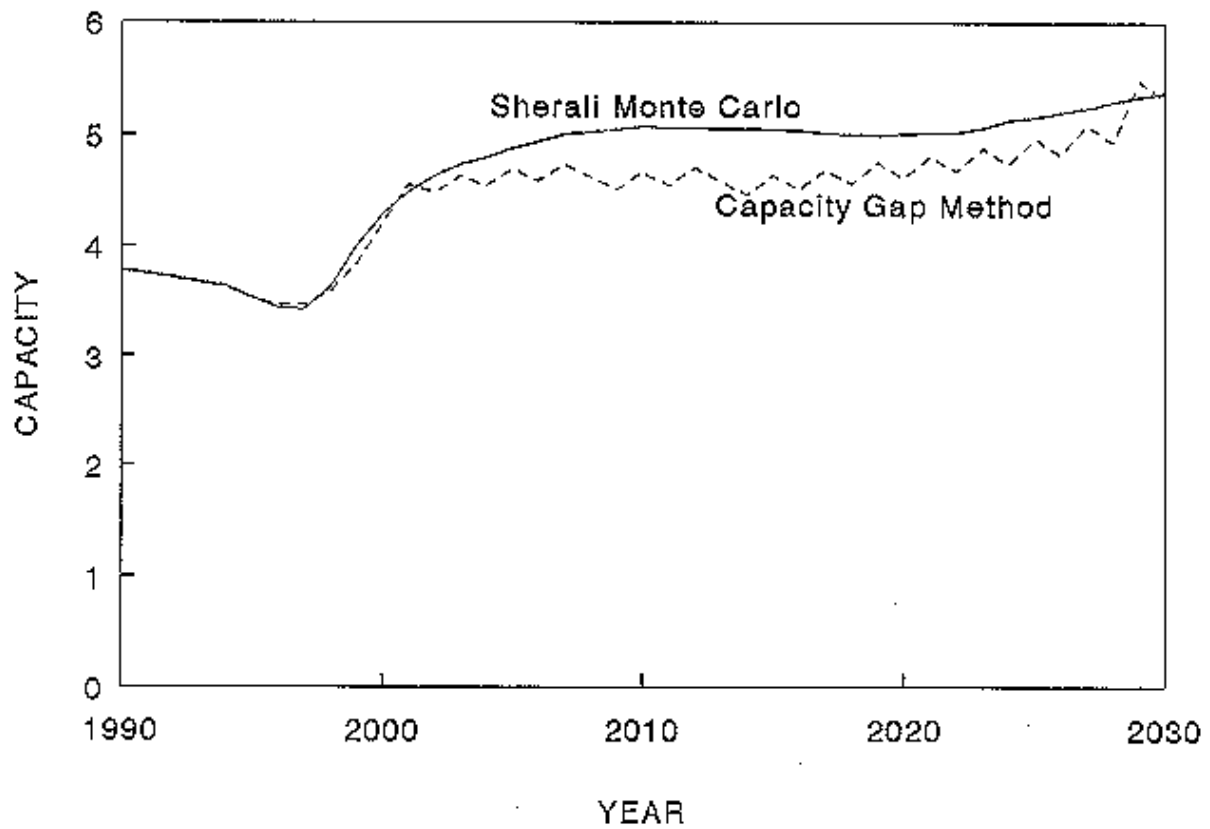


Figure C-3. Intermediate Capacity

Peak Capacity

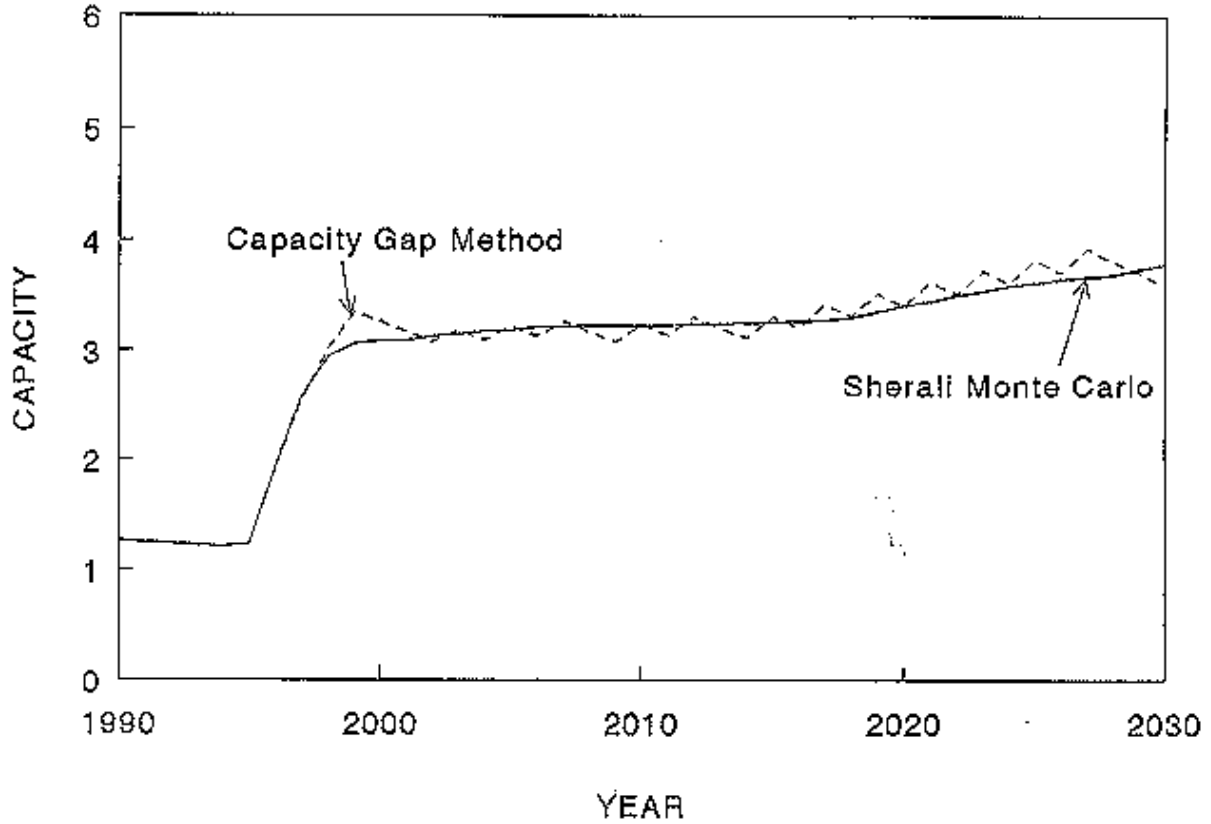


Figure C-4. Peak Capacity

In the heuristic solution, cost diversity is accomplished by a logit function which assumes that the nominal cost per unit new capacity of a given technology operating at a specified capacity utilization factor f , is

$$k_i = C_{ci} + C_{oi}u,$$

and that the various values of k_i are independent random variables generated by an underlying Weibull distribution with location parameter k_i and shape parameter γ (the same value of γ , -10, is used for all random variables) - see Appendix E for a discussion of the logit function. For the Weibull distribution, $\gamma = -10$, the mean and variance of the random variables k_i , associated with k_i , are

$$E\{K_i\} = \Gamma(1 - 1/\gamma)k_i = 0.95k_i$$

$$\sigma^2\{K_i\} = [\Gamma(1 - 2/\gamma) - \Gamma^2(1 - 1/\gamma)]k_i^2 = 0.01311k_i^2,$$

where Γ is the gamma function. Thus the standard deviation is approximately 11.5% of the nominal cost for $\gamma = -10$ (the square root 0.01311 is 0.1145).

Modeling the random cost structures in the Sherali method to exactly copy the logit structure is not possible since the Sherali method does not explicitly use the capacity utilization factor and there does not appear to be a known pair of independent distributions whose sum is Weibull.

However, we feel quite strongly that the results of the Monte Carlo simulations are not sensitive to the exact underlying cost probability distributions. For the Monte Carlo simulations, let κ_i and ω_i be the random variables associated with the capital and operating cost, respectively, for the i -th technology. We chose these random variables to be independent gaussian (normal) with mean and variance

$$\begin{aligned} E\{\kappa_i\} &= 0.95C_{ci}, \quad E\{\omega_i\} = 0.95C_{oi}, \\ \sigma^2\{\kappa_i\} &= 0.01311C_{ci}^2(C_{ci} + C_{oi})^2/(C_{ci}^2 + C_{oi}^2), \\ \sigma^2\{\omega_i\} &= 0.01311C_{oi}^2(C_{ci} + C_{oi})^2/(C_{ci}^2 + C_{oi}^2), \end{aligned}$$

resulting in the statistical properties

$$\begin{aligned} E\{\kappa_i + \omega_i\} &= 0.95(C_{ci} + C_{oi}), \\ \sigma^2\{\kappa_i + \omega_i\} &= 0.01311(C_{ci} + C_{oi})^2, \end{aligned}$$

that is, as though all technologies were operating at the value $u = 1$ for purposes of defining the underlying cost probability density functions. This formulation implies a somewhat larger variance for the Monte Carlo random variables than in the neuristic model, but should not affect the final results appreciably. As the absolute value of γ increases, the Weibull distribution tends to resemble the gaussian distribution. The resemblance is quite close at $\gamma = -10$.

As shown in Figure C-2, C-3, and C-4, the results of the capacity expansion methodology described in Appendix A, and used in the Sandia capacity expansion and energy production module, compare very favorably with the Sherali Monte Carlo results. In all these simulations, the look-ahead time and all construction times were set to five years.

APPENDIX D. Comparison of Electric Utility Capacity Expansion Projections Between Sandia's Capacity Expansion Model and EGEAS using an EGEAS Test Case

Date: July 28, 1992

To: Distribution

From: Mike Edenburn and Gene Aronson, Strategic Technologies Dept. (6904),
Sandia National Laboratories

Subject: Comparison of Electric Utility Capacity Expansion Projections Between
Sandia's Capacity Expansion Model and EGEAS using an EGEAS Test Case

Sandia's electric utility capacity expansion model has been developed to provide DOE/CE's Office of Utility Technologies with a sound analytical tool to assist in energy policy analysis. The model, which can be used as a module in more general energy analysis models, projects long term renewable energy technology (RET) expansion trends into regional electric utility markets. It explores the effects of energy policy options on utility capacity expansion trends. The model uses less detailed algorithms than models used by utilities for capacity expansion planning, but it follows their basic principles. Validation is an important part of our model development project. One validation exercise has been to compare our model's projections with those from a more comprehensive and generally accepted model. We have selected EPRI's (Electric Power Research Institute) EGEAS (Electric Generation Expansion Analysis System) for the comparison.

EGEAS was developed by EPRI and is used by several large U.S. electric utilities for capacity expansion planning. The EGEAS model is described in EPRI report EPRI EL-2561 published in August, 1982. Stone and Webster Management Consultants manage and distribute the model and coordinate an active users' group. Data for the test case was selected and supplied by Joel Halvorson of Stone and Webster, and he ran the test case using EGEAS to get results for comparison.

Previous validation exercises have addressed elements of the Sandia model: aggregated generation units, averaged intermittent source production data, a simplified production costing algorithm, and a simplified optimization process. The conclusion drawn from these exercises was that each of our simplified model elements is sufficiently accurate to be appropriate for use in a regional, policy analysis model, but it is possible that the inaccuracies in several "sufficiently accurate" elements working together can combine to make unrealistic projections. To explore this possibility, we have compared our model's results to those for a test case run using EGEAS. The test case was derived from standard test case R6112. Input for the test case is discussed below.

Existing, Under Construction, and New Generation Capacity

The EGEAS test case starts in 1987 with the existing and under construction capacity shown in Table 1. A more detailed listing is shown in Attachment A.

Table 1. Existing and Under Construction EGEAS Capacity (1987)

<u>Type</u>	<u>Units</u>	<u>Total Capacity MW</u>
<u>Existing</u>		
Nuclear	2	2400
Coal	12	3612
Oil-Steam	9	2596
Oil Combined Cycle	1	286
Oil Combustion Turbine	30	1594
Hydro	2	100
Pumped Hydro Storage	4	425
Photovoltaic	2	15
<u>Under Construction</u>		
Nuclear (on line 1990)	1	1200
Oil Combined Cycle (on line 1989 & 1992)	2	571

The EGEAS test case selected from the technologies listed in Table 2 for new capacity additions. For more details, see Attachment A.

Table 2. New Capacity Options for EGEAS

Nuclear-LWR
Coal-Advanced pulverized with FGD
Oil steam
Oil combustion turbine
Gas combined cycle, standard and advanced
Gas advanced combustion turbine
Pumped hydro storage
Photovoltaic

The Sandia model uses aggregated capacity values and does not consider individual units. It accounts for existing capacity and capacity under construction separately, but, for simplicity, we added capacity under construction to existing capacity for this test case. Detailed input data for the Sandia model is included in Attachment B.

Table 3. Sandia Model Existing Capacity (1987)

<u>Type</u>	<u>Capacity (MW)</u>
Nuclear	3600
Coal	3612
Oil Steam	2600
Oil Combined Cycle	860
Oil Combustion Turbine	1590
Hydro	100
Pumped Hydro Storage	394
Photovoltaic	15

To simplify our model's input, we assumed that new and existing units within a technology are identical and have the same parameter values except for coal. Old and new coal were treated as separate technologies. We restricted the new technology capacity expansion options for the Sandia model to those which we expected to be the most competitive. These capacity expansion options are shown in Table 4.

Table 4. Capacity Expansion Options for the Sandia Model

<u>Type</u>	<u>Corresponding EGEAS Technology</u>
Nuclear	Advanced LWR
Coal	Advanced Pulverized Coal with FGD
Oil Combined Cycle	Oil Combined Cycle
Oil Combustion Turbine	Oil Combustion Turbine
Gas Combined Cycle	Standard Gas Combined Cycle
Gas Combustion Turbine	Advanced Gas Combustion Turbine
Pumped Hydro Storage	Pumped Hydro Storage
Photovoltaic	Photovoltaic #2

We used the same parameter values for the Sandia model capacity expansion options that EGEAS used for its corresponding options to the extent possible. (These values are shown in the appendix.) There were some differences. The Sandia model does not consider a unit's reserve capacity or loading blocks. We treat interest during construction just like construction cost,

although, in reality, it is treated differently for tax purposes. We do not consider spinning reserve or startup costs. EGEAS's forced outage rates change with time while the Sandia model uses constant values. To account for changing forced outage rates, the Sandia model uses average values. There is a slight difference in how the two models compute depreciation for tax purposes. We used parameter values which most closely duplicated EGEAS depreciation schedules. In EGEAS, each generation unit has a service date when it first came on line and a plant life, and these two parameters determine when the plant will be retired. Since the Sandia model aggregates, it does not retire individual units. We were not able to accurately match EGEAS retirement schedules with simple retirement rates, so we altered the Sandia model to include EGEAS retirement schedules. To summarize, we attempted to duplicate parameter values used in EGEAS, but there are small differences.

Load and Intermittent Source Generation Data

Both models used a peak 1988 load of 9400 MW, a load growth rate of 1% per year, and a load profile defined by EGEAS's data file HOURLOAD.SYB. This load profile consists of 8736 hourly data points covering 364 days. The Sandia model will not generally use this large a data set. We used a "complete" year for the test case to avoid differences associated with data quantity so that we can concentrate on differences caused by model algorithms.

Photovoltaic generation was defined by EGEAS's data file HOURGENR.PV2. While not intermittent, hydro power generation is treated like intermittent generation because it is subtracted from the load to get a net load. There are a variety of hydro power types. Run-of-the-river hydro is intermittent with power generated when river flow is available, and this usually follows a seasonal pattern. At the other extreme, hydro power can be completely dispatchable and used at any time during the year. We assumed that hydro is dispatchable and we subtracted its power from the year's peak generation hours with the appropriate energy restriction.

Our model did not previously include energy storage, which is an important option in EGEAS. After testing several simple models for storage which did not work well, we designed one which "optimizes" storage use. Storage must be dispatched with an optimum schedule to obtain its full value. Simple models tended to displace the same generation technology during high load hours used for recharge during low load hours. Displacing and recharging with the same technology gives storage a net economic loss due to storage inefficiency. To get its full benefit, storage should only be used to displace a generation technology if the recharging technology's operating cost divided by storage efficiency is lower than the displaced technology's operating cost.

Our present storage model arranges daily loads in order of size. The highest load is paired with the lowest, the second highest with the second lowest, and etc. Displaced energy for the high load hour must be recharged during the low load hour in the pair. Storage power is adjusted, if necessary, to insure that the last unit of displaced energy is more valuable than the last unit of

recharge energy. The appropriate daily storage energy limit is applied. This scheme is not exactly optimum because it only allows discharge and recharge within hour pairs. Making discharge and recharge decisions across multiple hours is required to obtain a true optimum. Because it is not a true optimum, our storage algorithm may tend to slightly undervalue and thus underuse energy storage.

Comparison of Projections from the Two Models

It is unrealistic to expect identical results from Sandia's model and EGEAS. On the other hand, to be useful, results from the Sandia model should follow the same capacity expansion trends as those from EGEAS.

There are several reasons why identical results cannot be obtained:

1. Units are aggregated by technology in Sandia's model. EGEAS buys integral size units while the Sandia model can buy any size. EGEAS uses a retirement date for each unit while Sandia's model uses a retirement rate. These Sandia model simplifications are appropriate for a regional model but not for an individual utility.
2. The Sandia model uses a simplified production costing algorithm (instead of a probabilistic algorithm) which underestimates the energy generated by peaking plants. This will slightly bias the value of new capacity additions.
3. The Sandia model's optimization scheme is sub-optimal and will give slightly different results than a true optimization.
4. EGEAS optimizes over a 30 year time block and finds the optimum, integrated expansion plan. Selecting a particular plant depends on future as well as past capacity additions. Sandia's model optimizes one year at a time using leveled capital and operating cost over each plant's life. Its optimization accounts for existing but not for future capacity additions.
5. EGEAS uses much more detailed input data: escalating capital and operating cost schedules, reserve capacity, capacity blocks, changing forced outage rate schedules, special treatment of interest during construction, spinning reserve and startup costs (spinning reserve and startup cost were not used by EGEAS in the test case), and etc.
6. Sandia's model assumes cost diversity. The cost of a technology is not a single value and a technology will be selected for some capacity even though its most probable cost is slightly higher than a competitor's most probable cost. EGEAS does not use cost diversity. Cost diversity is not appropriate for a single utility model, but it is appropriate for a regional model.

The EGEAS model's dynamic programming option projects the capacity additions shown in Table 5.

Table 5. New Capacity Additions Projected by EGEAS

<u>Type</u>	<u>Size MW</u>	<u>Year</u>
Coal-Advanced Pulverized with FGD	750	1995
Coal- "	750	1997
Coal- "	750	1999
Coal- "	750	2001
Gas-Combined Cycle	220	2004
Gas- "	440	2005
Gas- "	440	2006
Gas- "	220	2007
Coal-Advanced Pulverized with FGD	750	2008
Storage-Pumped Hydro	350	2008
Storage- "	350	2010
Storage- "	350	2011
Gas-Combined Cycle	220	2011
Coal-Advanced Pulverized with FGD	750	2012
Coal- "	750	2013
Oil-Combustion Turbine	75	2015
Coal-Advanced Pulverized with FGD	750	2016
Gas-Advanced Combustion Turbine	130	2016
Oil-Combustion Turbine	75	2016
Oil- "	150	2017
Gas-Advanced Combustion Turbine	130	2017

Total capacity asset projections from EGEAS are plotted in Figure 1. Figure 2 shows the capacity assets projected by Sandia's model. At the end of the 30 year expansion period, the two models are in very close agreement. The main difference between the two models is in the timing of coal and gas combined cycle asset additions. EGEAS installs 3000 MW of coal between 1995 and 2001 followed by no new coal installations between 2002 and 2008. The Sandia model installs only 800 MW of coal between 1995 and 2001 but continues steady coal installation and catches up with EGEAS in 2008. The Sandia model lags EGEAS in coal installations, but it compensates by leading EGEAS in gas combined cycle installations. The difference in timing is probably due to EGEAS's ability to optimize over a 30 year time block in combination with its restraint to use specific unit sizes. A less significant difference is that the Sandia model installs more gas combustion turbines than EGEAS, in part because it uses a higher reserve margin than EGEAS and in part to help compensate for the time lag in coal expansion. In spite of these differences, agreement in trends between the two models is very good. While both models considered only one true intermittent renewable source--photovoltaics which neither model elected to install--the models agree closely on pumped hydro energy storage which is treated like

an intermittent source in the Sandia model's optimization process. We will discuss projections one technology at a time.

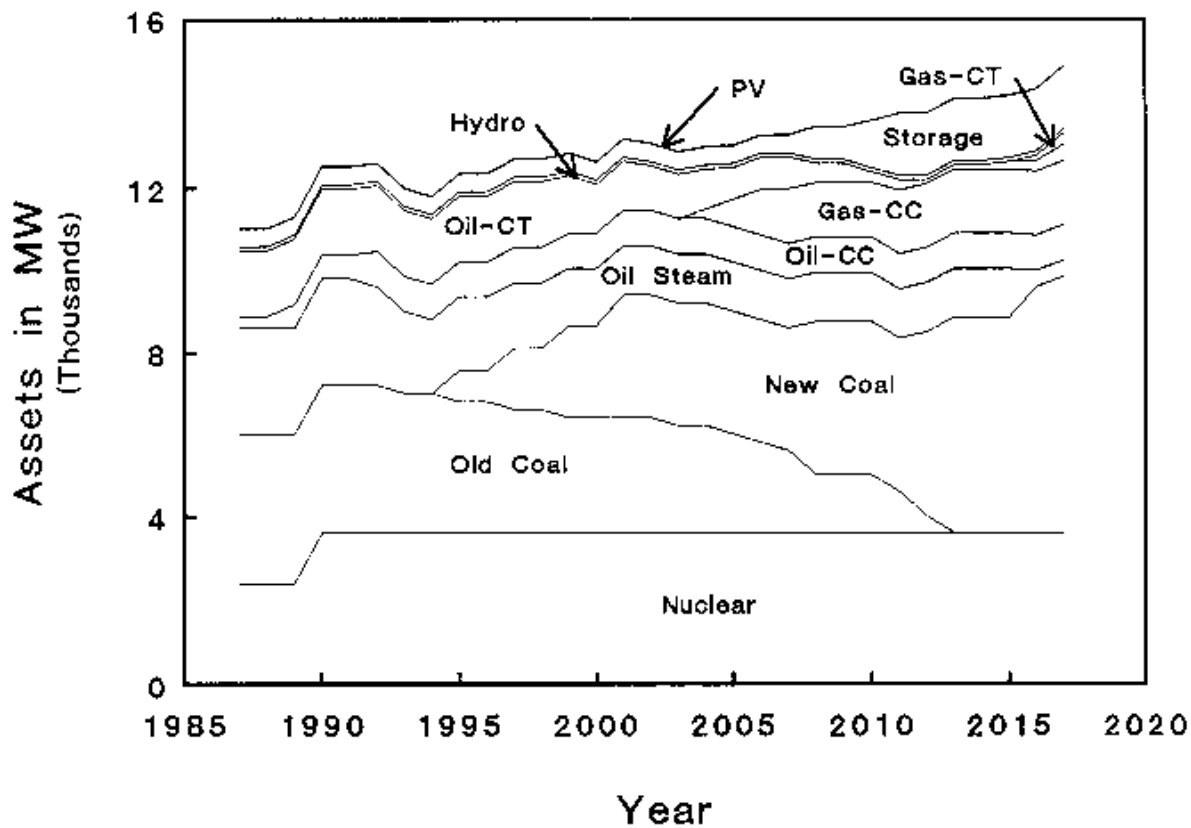


Figure D-1. EGEAS Test Case Assets (EGEAS)

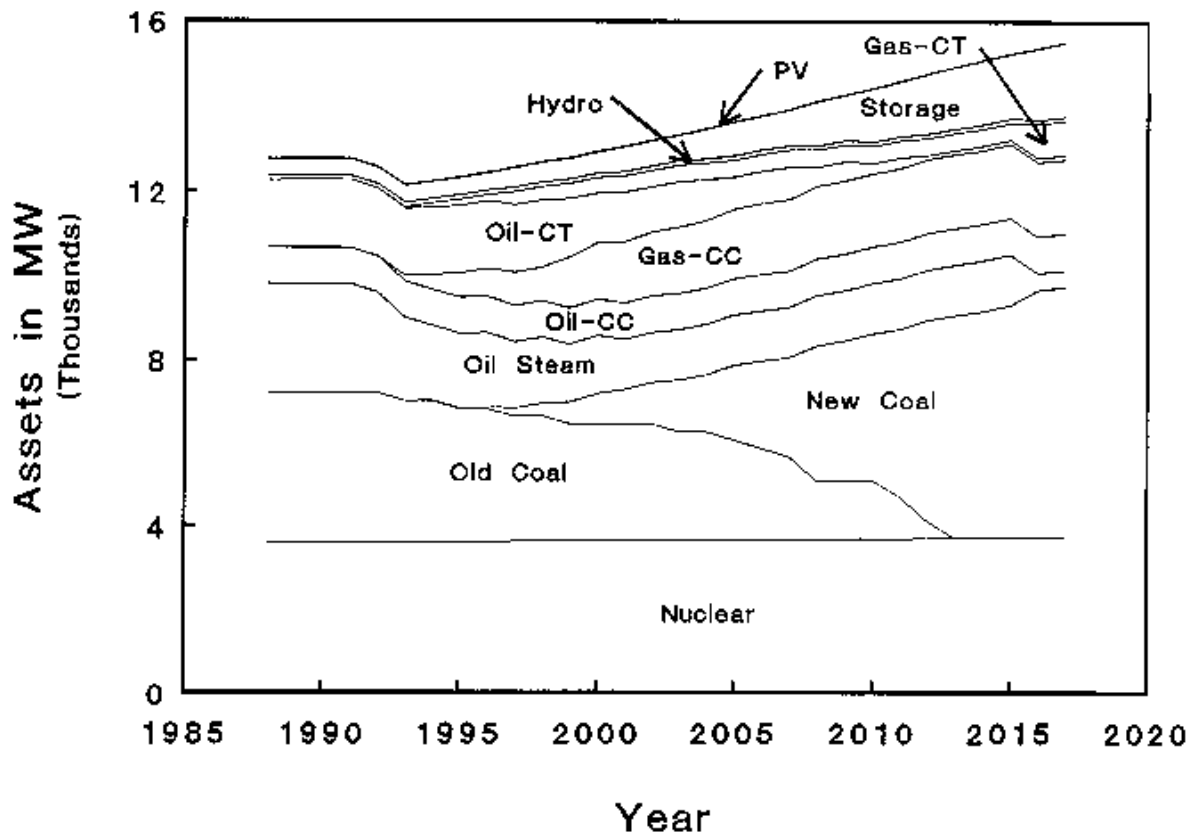


Figure D-2. EGEAS Test Case Assets (Sandia Model)

Nuclear--EGEAS projects that no new nuclear capacity will be added beyond that under construction in 1987. The Sandia model projects a very small nuclear addition due to cost diversity.

Coal--Coal capacity assets for the two models are compared in Figure 3. EGEAS builds 3000 MW of new coal plants in the six years between 1995 and 2001. Then, it builds no new coal plants until 2008. The Sandia model builds 800 MW of new coal plants between 1995 and 2001 but continues to build 2400 MW through 2008. In 2008, the coal assets for the two models are roughly equal. From 2008 to 2017 the two models agree very closely, and coal assets for the two models are nearly equal in 2017, the final year. As expected, the expansion details are different but the trends agree very well. Part of the detail difference is due to cost diversity. Reducing cost diversity increases coal expansion between 1995 and 2001 in Sandia's model, but not nearly enough to match EGEAS expansion for those years. We believe that most of the difference is due to EGEAS optimizing over a 30 year time block using specified unit sizes in contrast to Sandia's model optimizing one year at a time without unit size restrictions.

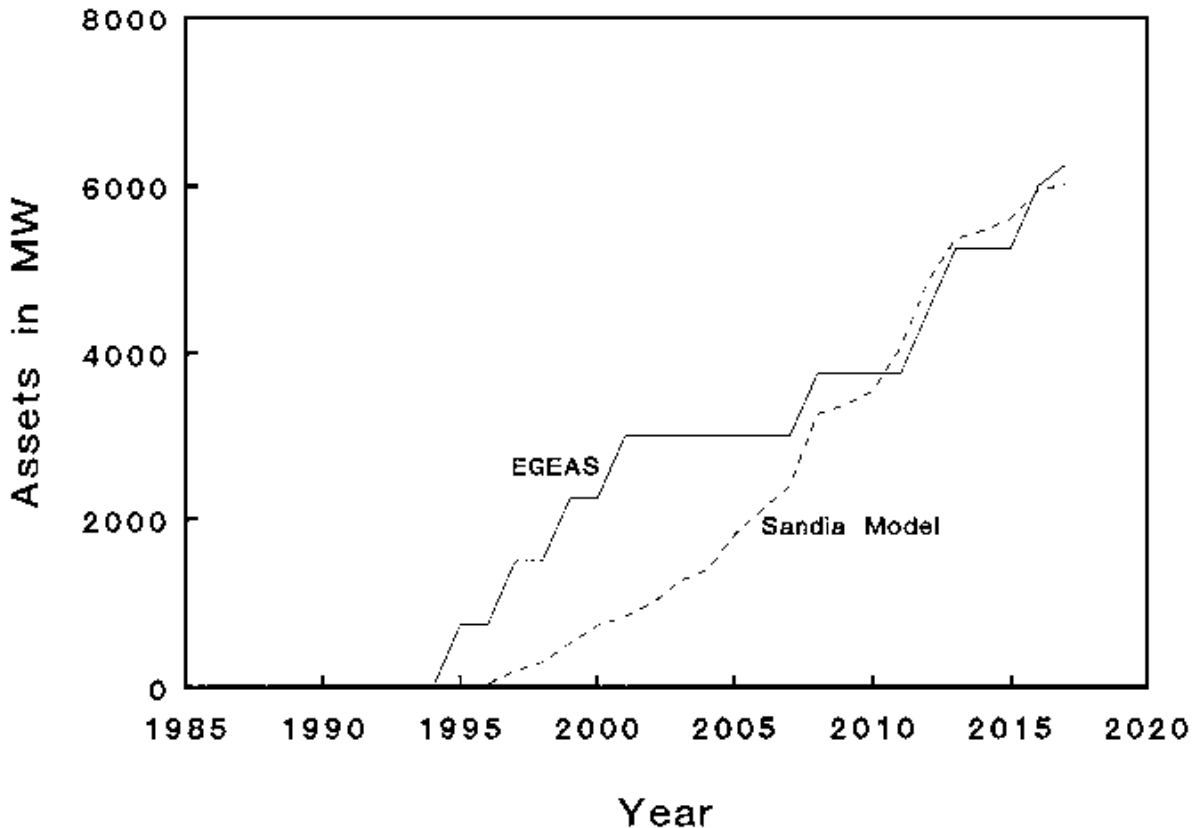


Figure D-3. EGEAS Test Case Comparison--New Coal

Oil-Steam--Neither model adds oil-steam capacity. Both models follow the same retirement trend because that was imposed upon them. Sandia's model might have added a little oil-steam capacity due to cost diversity, but oil-steam was not allowed to compete.

Oil Combined Cycle--Oil combined cycle is not a competitor in EGEAS. The Sandia model allows it to compete but only adds a very small amount because of cost diversity.

Gas Combined Cycle--Over the 30 year expansion period, EGEAS adds 1540 MW of gas combined cycle. Sandia's model adds 1750 MW. Trends for the two models are in good agreement, although installation timing is different. Sandia's model leads EGEAS in gas combined cycle expansion as can be seen in Figure 4. This lead compensates for its lag in coal expansion as discussed above. In Figure 5, we plot coal assets and the sum of coal and gas combined cycle assets for both models. The sums agree very well between the two models. Sandia's model projects that the sum of coal and gas combined cycle expansion will be slightly less than that projected by EGEAS between 1995 and 2001. This small difference is made up with gas combustion turbines in Sandia's model, explaining why gas turbines are introduced earlier by Sandia's model than by EGEAS. Why does EGEAS make a big coal expansion between 1995 and 2001 followed by a big gas combined cycle expansion between 2001 and 2008 while Sandia's model tends to project the reverse order? Gas combined cycle operating costs are escalating

faster than coal costs because of fuel cost escalation. This argues in favor of installing gas combined cycle plants earlier when they are less expensive is the trend projected by Sandia's model. We believe that EGEAS installs coal plants first because its optimization over a 30 year time block sees an advantage to installing coal plants between 1995 and 2001. The advantage is probably due to interfaces with other technologies scheduled for installation in the future.

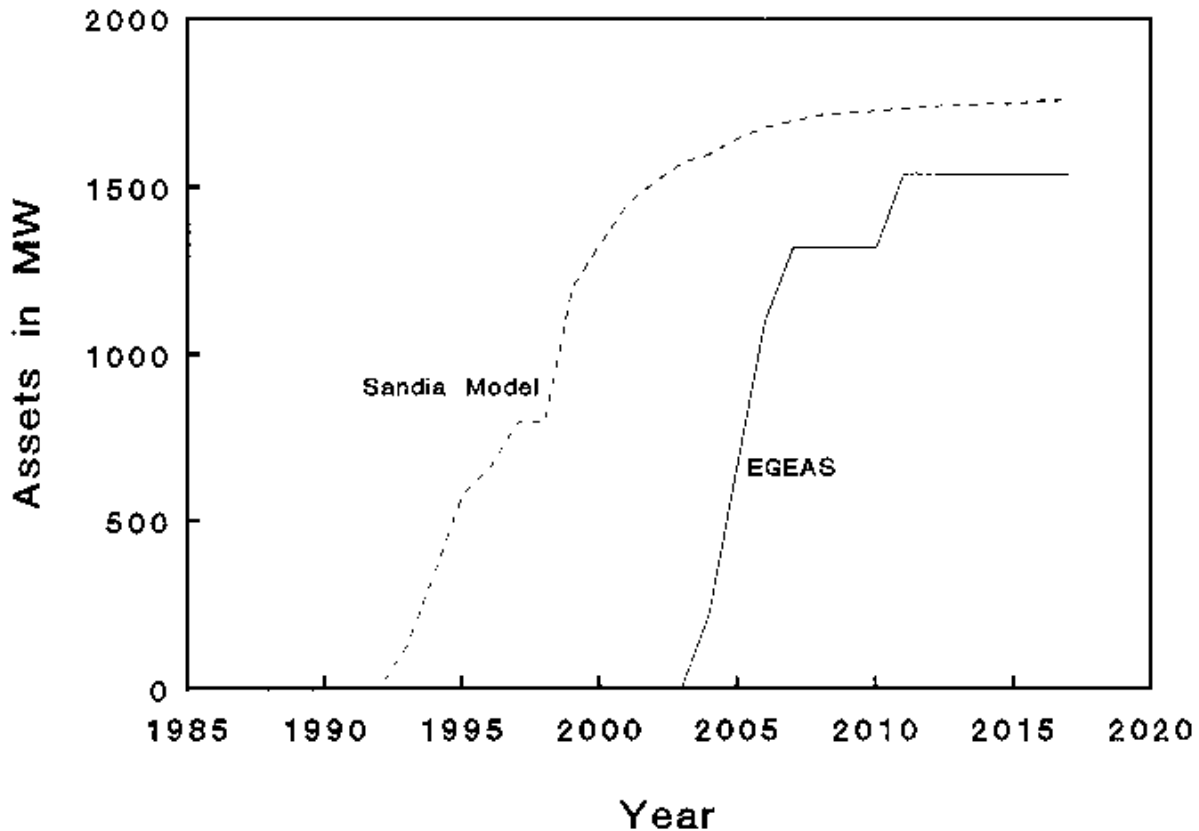


Figure D-4. EGEAS Test Case Asset Comparison--Gas Combined Cycle

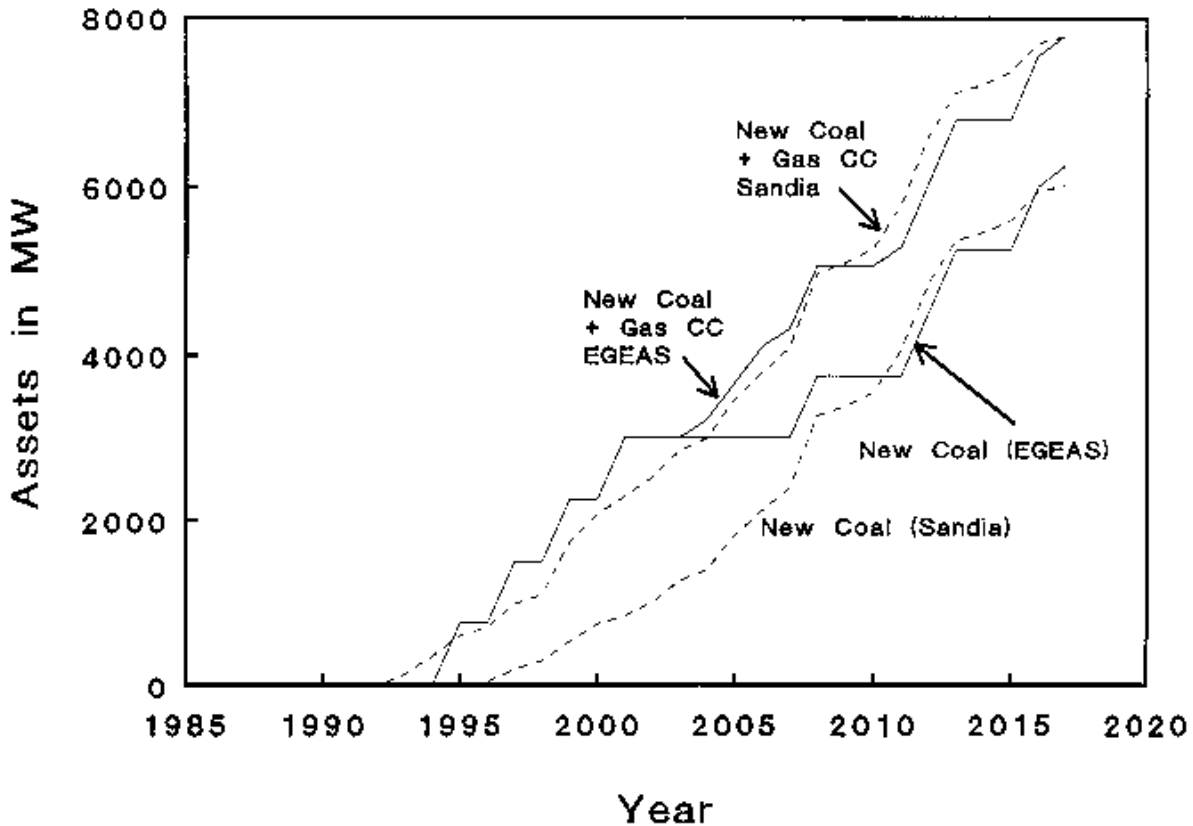
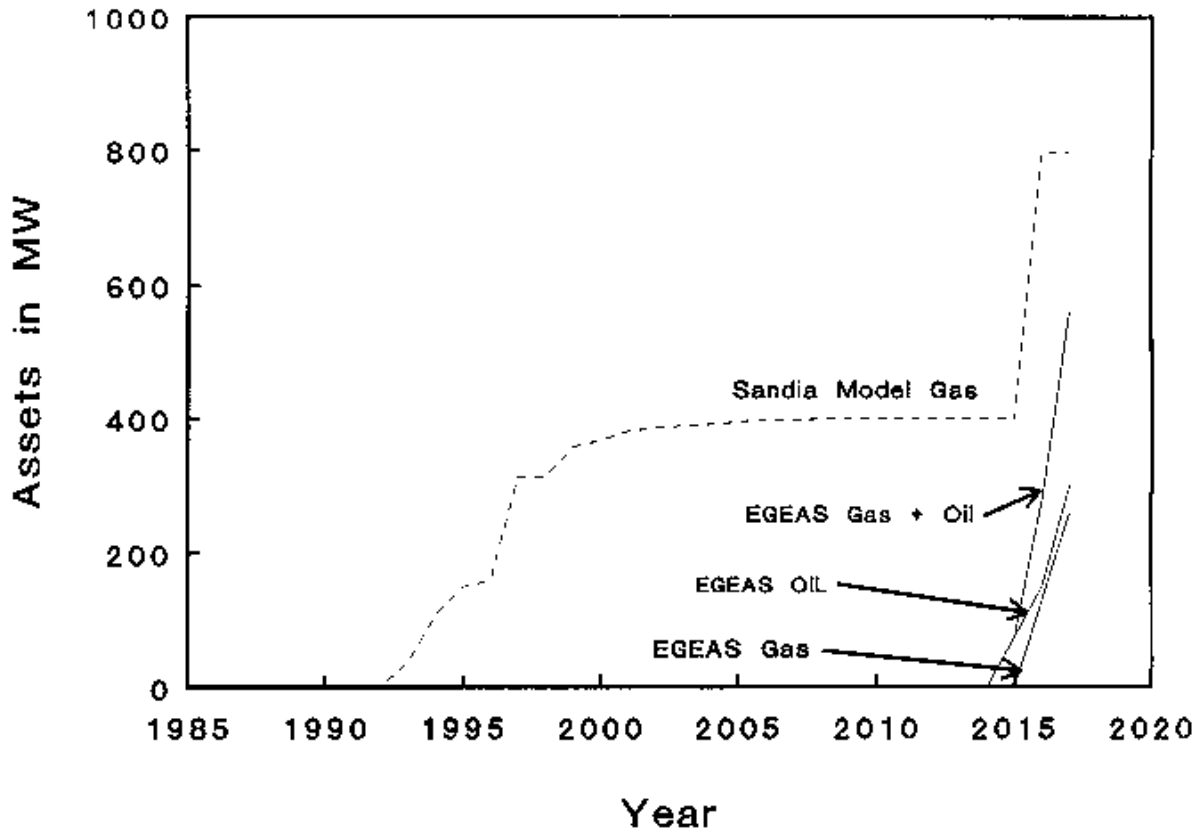


Figure D-5. Egeas Test Case Asset Comparison--New Coal + Gas Combined Cycle

Oil Combustion Turbines--EGEAS adds 300 MW of new oil combustion turbines at the end of the design period. Sandia's model adds almost no oil combustion turbines. What it does add is due to cost diversity. EGEAS adds oil combustion turbines because a limit was imposed on gas combustion turbines. Without the limit, gas combustion turbines would have been selected instead.

Gas Combustion Turbines--EGEAS adds 260 MW of gas combustion turbines at the end of the design period. The Sandia model adds 800 MW split between the 1994 to 2001 time period and the end of the design period. Part of the difference is due to our approximation for reserve margin which is higher than that used by EGEAS. Part of the difference is due to compensation for the Sandia model's lag in coal expansion between 1995 and 2001. Part of the difference is due to the Sandia model's cost diversity. Reducing diversity reduces gas turbine expansion. If oil and gas combustion turbines are combined, EGEAS adds a total of 560 MW compared to the Sandia model's 800. Results for both oil and gas combustion turbines are shown in Figure 6. Differences between the two models have several explanations, but the important observation is that the trends agree fairly well.



**Figure D-6. EGEAS Test Case Asset Comparison--
New Gas and Oil combustion Turbines**

Pumped Hydro Energy Storage--The two models agree very well for pumped hydro energy storage. This is particularly noteworthy because energy storage is not easy to model and because the Sandia model treats energy storage like an intermittent in its optimization process. Storage results are shown in Figure 7.

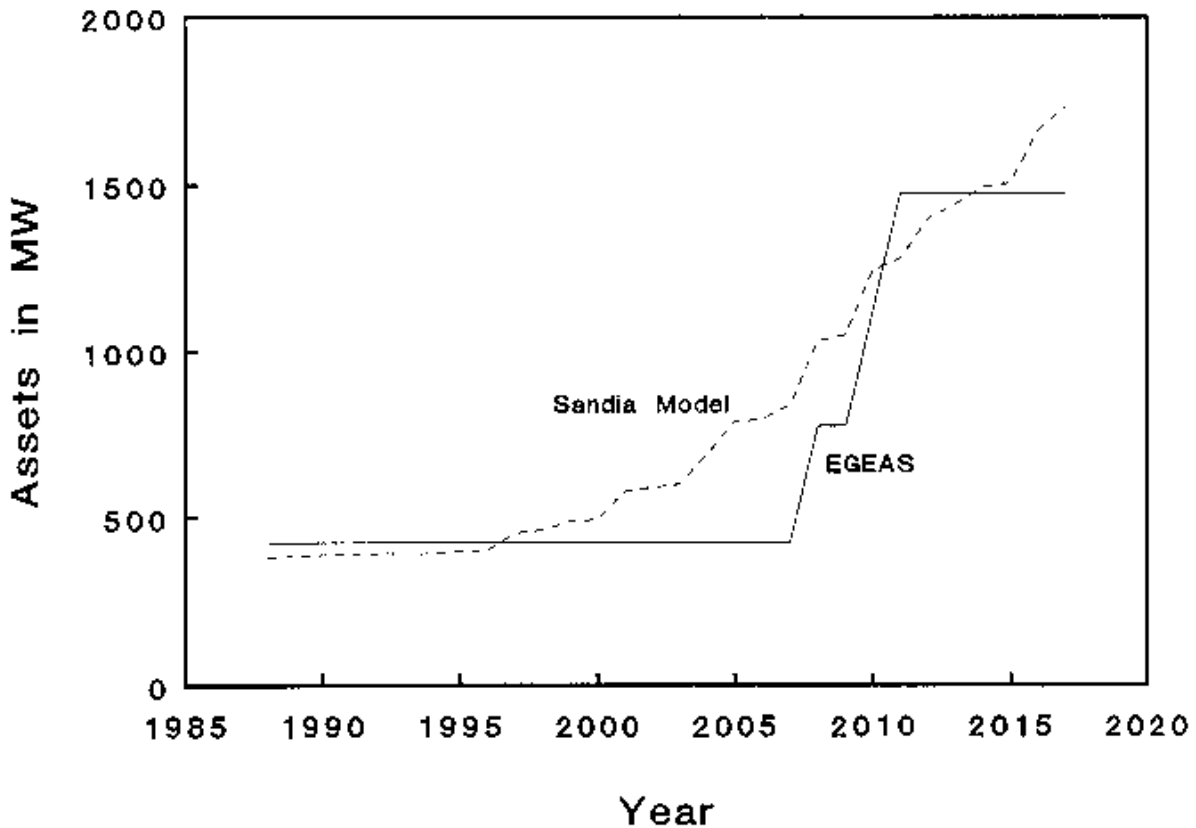


Figure D-7. EGEAS Test Case Asset Comparison--Pumped Hydro Storage

Our overall conclusion is that trends projected by Sandia's model agree very well with those projected by EGEAS. We believe that this is an important conclusion because it supports using a relatively simple but conceptually sound, regional, electric utility capacity expansion model for evaluating energy policy options.

Attachment A. Selected Parameter Values for EGEAS Electrical Generation Technologies

Existing Capacity in 1987

Type	#	Installed	Life	Capacity MW	Forced Outage	Scheduled Outage	Heat Rate BTU/kWh	Fuel Price \$/MBTU	Fuel Cost \$/kWh	Fuel Escal	Fixed O&M \$/kW-Yr	Variable &M \$/kWh
Nuclear	101	1981	40	1200	.149	.135	10,100	.76	.0077	.052	33.1	.00093
Nuclear	102	1983	40	1200	.149	.135	10,100	.76	.0077	.052	33.1	.00094
Coal	103	1968	40	600	.155	.115	9,800	1.61	.0158	.051	21.2	.00563
Coal	104	1972	40	600	.155	.115	9,800	1.61	.0158	.051	21.2	.00564
Coal	105	1971	40	400	.124	.096	9,910	1.61	.0160	.051	21.2	.00565
Coal	106	1973	40	400	.124	.096	9,910	1.61	.0160	.051	21.2	.00566
Coal	107	1953	40	202	.081	.058	10,460	1.61	.0168	.051	21.2	.00567
Coal	108	1955	40	202	.081	.058	10,460	1.61	.0168	.051	21.2	.00568
Coal	109	1957	40	202	.081	.058	10,460	1.61	.0168	.051	21.2	.00569
Coal	110	1959	40	202	.081	.089	10,460	1.61	.0168	.051	21.2	.00570
Coal	111	1963	40	201	.081	.058	10,460	1.61	.0168	.051	21.2	.00571
Coal	112	1965	40	201	.081	.058	10,460	1.61	.0168	.051	21.2	.00572
Coal	113	1966	40	201	.081	.058	10,460	1.61	.0168	.051	21.2	.00573
Coal	114	1967	40	201	.081	.058	10,460	1.61	.0168	.051	21.2	.00574
Oil-Steam	115	1976	40	800	.176	.077	9,000	3.68	.0331	.097	4.3	.00442
Oil-Steam	116	1979	40	400	.124	.096	9,300	3.68	.0342	.097	4.3	.00443
Oil-Steam	117	1952	40	200	.081	.058	9,745	3.68	.0359	.097	4.3	.00444
Oil-Steam	118	1953	40	200	.081	.058	9,745	3.68	.0359	.097	4.3	.00445
Oil-Steam	119	1953	40	200	.081	.058	9,745	3.68	.0359	.097	4.3	.00446
Oil-Steam	120	1954	40	199	.081	.058	9,745	3.68	.0359	.097	4.3	.00447
Oil-Steam	121	1957	40	199	.081	.058	9,745	3.68	.0359	.097	4.3	.00448
Oil-Steam	122	1958	40	199	.081	.058	9,745	3.68	.0359	.097	4.3	.00449
Oil-Steam	123	1961	40	199	.081	.058	9,745	3.68	.0359	.097	4.3	.00450
Oil Combined Cycle	158	1986	40	286	.100	.077	7,500	3.66	.0275	.097	7.0	.00192
Oil Combustion Turbine	124	1969	30	53	.105	.038	11,500	3.93	.0452	.097	.5	.00518
Oil Combustion Turbine	125	1969	30	53	.105	.038	11,500	3.93	.0452	.097	.5	.00519
Oil Combustion Turbine	126	1969	30	53	.105	.038	11,500	3.93	.0452	.097	.5	.00520
Oil Combustion Turbine	127	1969	30	53	.105	.038	11,500	3.93	.0452	.097	.5	.00521
Oil Combustion Turbine	128	1970	30	53	.105	.038	11,500	3.93	.0452	.097	.5	.00522
Oil Combustion Turbine	129	1970	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00523
Oil Combustion Turbine	130	1970	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00524
Oil Combustion Turbine	131	1970	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00525
Oil Combustion Turbine	132	1972	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00526
Oil Combustion Turbine	133	1972	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00527
Oil Combustion Turbine	134	1974	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00528
Oil Combustion Turbine	135	1974	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00529
Oil Combustion Turbine	136	1975	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00530
Oil Combustion Turbine	137	1975	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00531
Oil Combustion Turbine	138	1975	30	52	.105	.038	11,500	3.93	.0452	.097	.5	.00532
Oil Combustion Turbine	139	1975	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00533
Oil Combustion Turbine	140	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00534
Oil Combustion Turbine	141	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00535
Oil Combustion Turbine	142	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00536
Oil Combustion Turbine	143	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00537
Oil Combustion Turbine	144	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00538
Oil Combustion Turbine	145	1978	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00539
Oil Combustion Turbine	146	1980	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00540

Attachment A. Selected Parameter Values for EGEAS Electrical Generation Technologies (Cont.)

Existing Capacity in 1987

Type	#	Installed	Life	Capacity MW	Forced Outage	Scheduled Outage	Heat Rate BTU/kWh	Fuel Pric \$/MBTU	Fuel Cost \$/kWh	Fuel Escal	Fixed O&M \$/kW-Yr	Variable O&M \$/kWh
Oil Combustion Turbine	147	1980	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00541
Oil Combustion Turbine	148	1980	30	51	.105	.038	11,500	3.93	.0452	.097	.5	.00542
Oil Combustion Turbine	149	1980	30	50	.105	.038	11,500	3.93	.0452	.097	.5	.00543
Oil Combustion Turbine	150	1982	30	50	.105	.038	11,500	3.93	.0452	.097	.5	.00544
Oil Combustion Turbine	151	1982	30	50	.105	.038	11,500	3.93	.0452	.097	.5	.00545
Oil Combustion Turbine	152	1982	30	50	.105	.038	11,500	3.93	.0452	.097	.5	.00546
Oil Combustion Turbine	159	1987	40	100	.105	.038	9,500	3.66	.0348	.097	.5	.00547
Hydro	153	1983	50	55	.0075	.000	NA	NA	NA	NA	10.1	.00174
Hydro	154	1986	50	45	.0075	.000	NA	NA	NA	NA	10.1	.00175
Pumped Hydro Storage	155	1985	50	105	.015	.000	NA	NA	NA	NA	3.6	.00369
Pumped Hydro Storage	160	1980	50	90	.030	.000	NA	NA	NA	NA	3.6	.00370
Pumped Hydro Storage	161	1982	50	130	.020	.000	NA	NA	NA	NA	3.6	.00371
Pumped Hydro Storage	162	1987	50	100	.015	.000	NA	NA	NA	NA	3.6	.00372
Photovoltaic	156	1982	40	5	.100	.135	NA	NA	NA	NA	9.4	.00889
Photovoltaic	157	1982	40	10	.100	.135	NA	NA	NA	NA	9.4	.00890

Under Construction Capacity in 1987

Type	#	Installed	Life	Capacity MW	Forced Outage	Scheduled Outage	Heat Rate BTU/kWh	Fuel Pric \$/MBTU	Fuel Cost \$/kWh	Fuel Escal	Fixed O&M \$/kW-Yr	Variable O&M \$/kWh
Nuclear	163	1990	30	1200	.149	.135	10,100	.76	.0077	.052	33.1	.00093
Oil Combined Cycle	164	1989	40	286	.100	.077	7,500	3.66	.0275	.097	7.0	.00192
Oil Combined Cycle	165	1992	40	286	.100	.077	7,500	3.66	.0275	.097	7.0	.00191

Attachment A. Selected Parameter Values for EGEAS Electrical Generation Technologies (Cont.)

Capacity Expansion Options

Type	#	Installed Cost \$/kW	Life	Capacity MW	Forced Outage	Scheduled Outage	Heat Rate BTU/kWh	Fuel Pric \$/MBTU	Fuel Cost \$/kWh	Fuel Escal	Fixed O&M \$/kW-Yr	Variable O&M \$/kWh
Nuclear LWR	201	2952	30	1100	.213	.135	10,220	.76	.0078	.052	33.1	.00092
Nuclear LMFBR	202	2228	30	1100	.129	.135	9,050	.53	.0048	.052	33.1	.00090
Coal Steam with FGD	203	1264	40	500	.195	.096	9,850	1.61	.0159	.051	21.2	.00562
Coal Regenerative & FGD	204	1420	40	500	.184	.096	10,430	1.61	.0168	.051	21.7	.00562
Coal Adv Pulverized FGD	205	1266	40	750	.146	.096	8,570	1.61	.0138	.051	20.7	.00438
Coal Solid SRC	206	1053	40	500	.170	.096	9,400	4.57	.0430	.051	7.3	.00753
Coal Atmos Fluid Bed	207	1214	40	500	.164	.096	9,710	1.61	.0156	.051	17.6	.00697
Coal Presur Fluid Bed	208	1494	40	250	.157	.096	9,421	1.61	.0152	.051	31.1	.00652
Coal Gas/CC TEX	209	1470	40	600	.128	.077	9,010	1.61	.0145	.051	30.5	.00326
Oil Steam	210	626	30	500	.170	.096	9,400	2.52	.0237	.096	4.3	.00441
Gas Combined Cycle	211	489	30	220	.049	.077	8,150	2.23	.0180	.100	7.0	.00191
Gas Adv Combined Cycle	212	530	30	390	.025	.077	7,900	2.23	.0176	.100	8.7	.00191
Oil Combustion Turbine	213	323	30	75	.043	.038	11,800	2.52	.0300	.096	.5	.00517
Gas Adv Combustion Turb	214	299	30	130	.043	.038	11,000	2.23	.0250	.100	.5	.00449
Oil Fuel Cell	215	1512	30	10	.114	.038	8,300	3.66	.0304	.097	22.6	.00753
Oil Advanced Fuel Cell	216	1403	30	2	.074	.038	6,450	3.66	.0236	.097	5.4	.02034
Hydro	217	1659	50	100	.029	.000	NA	NA	NA	NA	10.1	.00173
Coal Gas (Hydro)	218	1385	30	600	.128	.077	9,010	1.61	.0145	.051	30.6	.00327
Pumped Hydro Storage	219	770	50	350	.050	.038	NA	NA	NA	NA	3.6	.00368
Comp Air Rock Cav Stor	220	678	25	220	.056	.038	4,000	3.93	.0157	.097	2.2	.00191
Battery Storage	221	912	30	20	.025	.038	NA	NA	NA	NA	1.5	.00728
Photovoltaic # 1	222	2809	40	5	.054	.135	NA	NA	NA	NA	9.4	.00888
Photovoltaic # 2	223	2850	40	6	.048	.135	NA	NA	NA	NA	8.5	.00720

Attachment B. Sandia Electric Utility Capacity Expansion Model Parameters, EGEAS Test Case

<u>Technology Parameters</u>											
	<u>Nuclear</u>	<u>Old Coal</u>	<u>New Coal</u>	<u>Oil-Steam</u>	<u>Oil-CC</u>	<u>Oil-CT</u>	<u>Gas-CC</u>	<u>Gas-CT</u>	<u>Hydro</u>	<u>Storage</u>	<u>Photovoltaic</u>
Type	Adv LWR		Adv Pulv		Combnd Cyc	Combst Trb	Combnd Cyc	Combst Trb		Pump hydro	PV2
Initial Capacity MW	3600	3612	0	2600	860	1590	0	0	100	382	15
Capital Cost \$/kW	2952	No New	1266	No New	628	323	489	299	No New	923	2920
Capital Cost Escalation	0	NA	0	NA	-.01	0	-.01	0	NA	-.01	0
System Life Yr	30	40	40	40	40	30	30	30	50	50	40
Energy Capacity GWh	NA	NA	NA	NA	NA	NA	NA	NA	430	2.61	NA
Storage Efficiency	NA	NA	NA	NA	NA	NA	NA	NA	NA	.75	NA
O&M Fixed Rate \$/kW-Yr	33.1	21.2	20.7	4.3	7.0	0.5	7.0	0.5	10.1	3.6	8.5
O&M Variable Rate \$/kWh	.00092	.00568	.00438	.0045	.00191	.00517	.00191	.00449	.00173	.00368	.00720
O&M Escalation	.02	.01	.01	0	-.005	.01	-.005	.01	-.01	-.01	.01
Heat Rate BTU/kWh	10220	10100	8570	9450	7500	11800	8150	11000	NA	NA	NA
Base Fuel Price \$/MBTU	0.76	1.61	1.61	3.68	3.66	2.52	2.23	2.23	NA	NA	NA
Initial Fuel Cost \$/kWh	.0078	.0163	.0138	.0348	.0275	.030	.018	.025	NA	NA	NA
Fuel Escalation	.002	.001	.001	.045	.045	.044	.048	.048	NA	NA	NA
Forced Outage Rate	.249	.142	.171	.137	.100	.043	.049	.043	.000	.000	.000
Scheduled Outage Rate	.135	.089	.096	.070	.077	.038	.077	.038	.000	.000	.000
Depreciation Period Yr	16	NA	16	NA	21	16	21	16	NA	21	16
Construction Time Yr	8	NA	4	NA	2	1	2	1	NA	8	2
Retirement Rate 1/Yr	.00	Schedule	.00	Schedule	.00	Schedule	.00	.00	.00	.00	.00

General Economic Parameters (Same for all technologies in this test case)

Salvage Value \$/kW	0
General Inflation Rate	.05
Fed Income Tax Rate	.34
State Income Tax Rate	.04
Insurance Rate	.01
Price Year	1987
Discount Rate	.10
Loan Payment Period Yr	30
Loan Interest Rate	.07
Down Payment Fraction	.38
Property Tax Rate	.01
Fed Invest Tax Credit	0
State Invest Tax Credit	0
Depreciation Method	1.5 Declining Balance switching to Line
Energy Tax Credit	0

APPENDIX E. The Logit Function

The material in this appendix is extracted, in modified form, from [Resiter, 1982]. Suppose a decision maker has several options to supply a certain need. In our case, he may choose among different technologies to build physical assets to satisfy (electrical) energy demand. In a very natural way, he would choose the technology with the least marginal cost. Suppose there are N choices, and their associated marginal costs are c_n , $n = 1, \dots, N$. Of course, any decision maker would exclusively choose the least-cost technology. All other decision makers would also choose this least-cost option, and all other options would be excluded from any market share. However, in reality, all (or almost all) technologies will have some partial share of the market, and these shares will change with time as the various costs change.

Consider a state or region with many energy suppliers, each facing a unique set of costs. Each supplier chooses the technology which is least cost to him in some sense. Implied here is that cost itself, while an important consideration, may not be the only variable which determines choice for any particular supplier. Also, a supplier may have some singular situation where the actual cost of a technology to him is not the same as the cost to other suppliers. In the aggregate set of costs to all suppliers, each technology has a distribution of costs instead of one fixed cost. If these distributions are broad enough to overlap, it is possible that all technologies will be chosen to some degree.

Let a_n be the market share of the n -th technology. The sum of the shares must be unity; that is

$$\sum a_n = 1,$$

where the sum is from 1 to N . Since each supplier will choose the least cost (to him) option, the market share, a_n , for each option is the probability that the option has a lower cost than any of the competing options. The market share for the first option is

$$a_1 = \int_{u_1}^{\infty} \int_{u_1}^{\infty} du_1 \int_{u_1}^{\infty} du_2 \cdots \int_{u_1}^{\infty} du_N f(u),$$

where u_n is the distributed cost of the n -th technology, $f(u)du$ is the joint probability that the cost is in the region du about u , and $du = du_1 du_2 \cdots du_N$. Since the order of technologies is arbitrary, solution for a_1 is equivalent to solution for all shares.

Theoretically, we can create a joint probability density function for the technologies and perform the multiple integration above. In practice, however, this is a difficult task for an arbitrary joint probability density function. To simplify the integrations, a joint Weibull distribution is used; that is,

$$f(u) = \Pi (\gamma/C_n) (u_n/c_n)^{\gamma-1} \exp[-(u_n/c_n)^\gamma], (c_n > 0).$$

The product (Π) is over the N choices. The parameter γ determines (inversely) the broadness of the distribution, and c_n is related to the average cost of the n -th technology. For a single variable, the Weibull density function translated to the positive domain. As γ increases, the width of the density narrows and becomes more gaussian in shape.

Let δ_n be the average cost of the n -th technology. We get

$$\delta_n = \int_0^{\infty} du_n u_n (\gamma/c_n)(u_n/c_n)^{\gamma-1} \exp[-(u_n/c_n)^{\gamma}].$$

The integration yields

$$\delta_n = c_n \Gamma(1 + 1/\gamma),$$

where Γ is the Gamma function. As γ becomes large, the distribution become more peaked and the average cost, δ_n , approaches c_n , since $\Gamma(1) = 1$. The variance of the cost is given by

$$v_n = c_n^2 [\Gamma(1 + 2/\gamma) - \Gamma^2(1 + 1/\gamma)].$$

For $\gamma = 10$, the standard deviation is

$$\delta_n(\gamma = 10) = 0.114457 c_n,$$

that is, the one standard deviation band is $\pm 11.4\%$ about c_n .

We define the intermediate result

$$h_n = \int_{u_1}^{\infty} du_n (\gamma/c_n)(u_n/c_n)^{\gamma-1} \exp[-(u_n/c_n)^{\gamma}] = \exp[-(u_1/c_n)^{\gamma}].$$

Expressing the joint probability density function of technology costs as a Weibull distribution, interchanging integration order, and using the intermediate result in the evaluation of the market share gives

$$a_1 = \int_0^{\infty} du_1 (\gamma/c_1) (u_1/c_1)^{\gamma-1} h_n = c_1^{-\gamma} / \Sigma(c_n^{-\gamma}).$$

This is the logit function for market share of the “first” technology. The market share for the

m-th technology is obtained by replacing c_1 with c_m above. We repeat that c_n approaches the average value of the n-th technology’s cost as γ approaches infinity. The approach is quite rapid. For example, $\Gamma(1+1/10) = 0.951$. Also, the standard deviation approaches zero as γ goes to infinity.

The logit formulation described here is a special form of a more general logit describes in [Ben-Akiva, 1985]. The more general formulation assumes that the costs are drawn from a Gumbel distribution. The special formulation assumes that the random costs obey the Gumbel distribution, with a utility function which is the logarithm of the cost, yielding the Weibull distribution.

APPENDIX F. Summary from Evaluation of Tools for Renewable Energy

Policy Analysis: The Ten Federal Region Model, April 1994

Summary of Findings

The TFRM is an appropriate and valuable tool for conducting energy policy analyses of renewable energy scenarios. In its current form, the model requires a user who has invested considerable time in learning about model operation. The panel feels that with moderate effort, the model could be made substantially more user-friendly. This effort includes both streamlining and developing menus of the input procedures, as well as providing more comprehensive displays and post-processor interpretation of the outputs.

Intended Applications

TFRM was build to provide relatively quick turnaround results for an analyst who wants to conduct a somewhat detailed study of the impacts of renewables on a specific set of federal regions.

The evaluation panel feels that the TRFM provides a new kind of model that is intended to deal with renewable energy technologies in the context of regional electric systems. Some of the renewable energy issues that can be

investigated include the effects of capital cost and operating cost improvements, renewable tax incentives, fossil tax disincentives, efficiency improvements, regional variations in performances and site availability, competition between renewables, and other policies and issues.

The panel feels that the greatest value for this model is in the mid-to-far term. It will require some costs to develop, refine, test, maintain and make it into a user-friendly tool that will be accessible to a wide community of analysts. The TFRM is dependent upon the quality of input data, support analysis from overview models (such as the PERI REP model), and the familiarity of the user with the constraints and requirements of the model. The panel feels the limitations of TFRM will lessen in time, if additional work is conducted to improve the elements and usability of the model.

Structure

The structure of the TFRM was somewhat dictated by the initial assumption that a relatively quick turnaround regional model was needed to investigate the impacts of renewable energy technologies on the electric supply sectors. Feedbacks of cost energy to change the level of demand, and other feedback relations, must be accomplished by the user in out-of-model feasibility checks, output-to-input calculations, and additional scenarios. Occasionally, some model results are dictated by constraints and ratios, such as with renewable growth rates of 20 percent per year for attractive technologies. For the most part, however, the non-linear optimal search of the TFRM leaves most variables in the active basis and is much less directed by constraints than linear programming or other dynamically solved methods.

Several features of the model (e.g., the capacity expansion, dispatching, and especially the renewables areas) employ methods that differ from previous modeling approaches and are very creative and innovative in nature. The major advantage to having a different methodology is that it may offer new insights. The disadvantage is a public relations problem in educating analysts about the uses and applicability of the new methodology.

One major concern of the panel was the way in which the renewable space was searched to find an optimum allocation of available renewables. The concern is that the whole economic and policy space be searched. Although it is a little hard to determine from the documentation, it appears as if the search is beginning at the origin, or the zero use of renewables point. If the model then settles in any local optimum, it will probably be in the vicinity of the start of the search, and this would bias against the use of renewables.

Demand

Demand modeling requires close attention from the user; it is entirely exogenous. Conservation, independent producers, and demand-side management effects must all be backed out of the load seen by the electric system. Without this attention, the model will obviously bias in favor of supply-side solutions, including renewables. A helpful addition here might be to use a post-processor to

generate the demands that would be consistent with costs of electricity in various years. The user could then immediately see if changes in demand inputs were necessary. There is also some concern about the accuracy with which demand seasonality is modeled and the way that correlations are missed with seasonal fuel cost variations and seasonal renewable performance variations.

Capacity Expansion

The capacity expansion offers a very creative, alternative approach to other methodologies. It incorporates renewable resource depletion. It is well documented and has been validated against the Electric Generation Expansion Analysis Systems (EGEAS), a widely used electric industry expansion tool.⁵

Regional models are, however, difficult to validate against reality. The gap method, in particular, needs additional documentation, especially with regard to its problems: occasionally choosing uneconomic technologies, periods of disequilibrium, and biases. Repowering, especially repowering with combined cycles, also needs to be offered as an alternative to retirement.

Reliability

The conceptual approach to reliability in TFRM is an important improvement over the full-capacity/no capacity credit approaches that some other models use for intermittent renewable energy technologies. There are, however, some issues and weaknesses that require investigation. The use of intermittent renewables as negative loads makes some reliability and reserve issues more difficult to study. This treatment also does not account for forced outages as a function of unit

size or correlation of renewable energy productions.

The biases are difficult to sort out. Not accounting for some renewable technology reliability problems would tend to overestimate the use of renewables. However, biases toward lower reserve margins and lack of unit-size outage considerations would bias against renewables.

Dispatch

The dispatch logic of the TFRM is a traditional, deterministic, merit order dispatch. It seems to fit the renewables' needs impressively, and reacts properly to many different sensitivity tests.

It seems clear that with the national screening objective, the TFRM has to operate on regions (10 versus 13 regions is a debatable issue). And with regional modeling, it seems appropriate to use a deterministic technique, rather than a laborious probabilistic method.

The modelers are to be commended for testing their dispatching model against a Booth-Baleriaux probabilistic method and against a Lilienthal probabilistic method.⁶ The method used in the TFRM consistently underestimates energy displacement from gas turbines.⁷ Based upon a November 15, 1993, briefing by Sandia staff, the TFRM method underestimates these peaking energies displaced by wind and photovoltaics by a factor of 4 to 6. The approximation used probably is a little crude at the peak upswings. The quantities and costs are small (about 2 percent), but still worth concern if storage or peaking renewables are being modeled, or if there is a significant quantity

of renewables. The bias here is toward the use of more gas turbines, and less attractive renewables.

It is clear that with a substantial amount of intermittent renewable capacity, such as wind and solar, that a system or region might need more than the usual 7 percent spinning reserve. The right value may even be as high as 15 to 20 percent. In order that the spinning reserve be tied to the renewable capacity decision, it might be necessary to construct renewable turbine hybrids or renewable storage hybrids.

The TFRM results are often tightly constrained by operating and capacity assumptions. The operator must be aware of pressures and strains within the model. For this reason, it seems very important that the model output routinely print capacity factors (or percentage operating levels), cost of electricity, and other outputs that will make it easier for the user to make exogenous feedbacks.

Storage

In the comparison of the TFRM with EGEAS, the TFRM builds about 80 percent more pumped storage in the year 2006, but is about 10 percent lower by the 2012. This should be considered to be a bias in favor of building storage in the near term.

Storage may not be an important issue to correct if the questions revolve around renewables. However, there are two indications from the storage model run that storage may not be handled properly in the model. With the use of storage, the decrease in the use of baseload coal is counterintuitive, as is the increase, especially of the peaking gas turbines. The

modelers have looked at this and determined that this behavior is appropriate since, given the numbers in the trial run, coal is competitive with combined cycle at capacity factors as low as 25 percent.

Hydro- storage is added in the storage scenario that was run, but the cumulative capital costs and the cumulative operating costs are higher, leading to some question about why it was built. The explanation for this problem seems to come from the fact that, although not optimal in the current year, storage is economic in the long-term average. It is impressive that the model can capture such subtle concepts.

much greater accuracy in this area.

However, the model does not take into account the varying cost of capital by utility type, private or public. Some of the financial risks of new technologies are not accounted for, as they are in the REP model. A better study of the value of gamma (the cost diversity parameter γ) would be helpful. It appears that the TFRM results are in nominal dollars, but this requires further checking into the dollars and the accounting.

Transmission

TFRM has no real transmission modeling capability. It is recommended that this model incorporate a technique similar to that used by the REP model. Its simulations look reasonable and appear to be consistent with areas where there are good data, such as California.

Finances

The model incorporates technological and financial risks in a rudimentary way. Models that do not include these risks at all are likely to miss the main issue involved in the selection of renewables. Risk-less models will overestimate the use of renewables, and so TFRM has

Environmental Concerns

The TRFM does an excellent job in modeling the effects of the various carbon tax possibilities. On other environmental issues, however, the model may have some difficulties. One such area is that the total sulfur ceilings of the Clean Air Act can be exceeded in the model. These would probably have to be modeled with surrogate sulfur taxes, which would have to be adjusted until the sulfur caps were met.

Another untreated issue is the total life-cycle carbon implicit in the construction of facilities, although the carbon implicit in the production of fuels was accounted for in the trial runs. National carbon-limiting scenarios would have to take account of these implicit carbon emissions. The costs of materials and fuels would also go up with carbon taxes. This is a data problem rather than a methodological problem.

Additional untreated issues include land use, aesthetics, habitat destruction, and many other issues which are not amenable to a national modeling methodology. Values or proxy values must be generated before such externalities could be analyzed.

It is difficult to approximate the bias involved in not treating these environmental issues. Not including regional or nation sulfur caps would bias against renewables. Life-cycle carbon accounting would probably bias slightly in favor of existing units. Land use, aesthetics, and habitat concerns might bias against renewables.

Usability

The temptation seems to be to make the TFRM act like an exact utility planning model, such as EGEAS. There are several reasons why this would not be the ideal model. First, EGEAS, and other more detailed utility capacity planning models, were developed to suggest the *next optimal unit to add to a system*. Putting together a whole string of such next optimal units and adding the other utilities in a region would not provide a good predictor of the future of that region. It would be knife-edge in its selection of generation types, that is, all of one kind. It would not capture the risks, financial or technical, or the fuel diversity which is another important risk hedge used by utility planners. In short, a more statistical approach will do a far better job of forecasting regional capacity planning. TFRM incorporates those more statistical techniques. Not only would the addition of individual utilities and individual units be the wrong direction for FTRM to take, but it would make the model unusable for simulations of regions or the United States.

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